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The role and regulation of digital credit

Mixed-methods evidence on welfare effects in Kenya

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Abstract

Mobile money has enabled a proliferation of digital lenders in developing countries, yet evidence on their welfare effects remains limited. We examine the role and regulation of digital credit in Kenya, combining a propensity-scored difference-in-differences analysis of survey data with qualitative fieldwork in Nairobi. Qualitative findings suggest that digital credit primarily functions as emergency finance and a consumption-smoothing device, driven by underdeveloped social security and high income volatility. Welfare effects are heterogenous: liquidity-constrained borrowers with stable incomes can use it productively, while those with volatile incomes are more likely to fall into overindebtedness. Household survey analysis indicates a limited regulatory impact on borrower financial health and indebtedness. A slight decrease in debt distress is observed among high-exposure counties, while no significant effects on other outcomes. Qualitative evidence attributes the lack of transformative effects to oversight difficulties and borrowers' urgent liquidity needs maintaining demand for unlicensed lenders. Market formalisation, an improved credit information environment and reduced debt shaming nevertheless emerged as positive regulatory outcomes. The findings illuminate the limits of consumer protection regulation under conditions of structural vulnerability, the importance of enforcement capacity in regulatory implementation, and the potential for self-regulation as a complement to formal oversight. This study provides the first mixed-methods analysis of Kenya's 2022 Digital Credit Provider Regulations and their effects on borrower welfare, contributing to the literature on digital financial services and their regulation.

Keywords: digital credit, regulation, mixed methods, welfare effects, financial inclusion, Kenya

JEL Classification: G21, G28, G51, O16, O17

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Artificial intelligence statement

Artificial intelligence (AI) has primarily been used to generate, modify and correct Stata code to facilitate the quantitative analysis. Generative AI has also, to a lesser extent, been applied to enhance the language in the thesis. Claude has been the AI agent of preference, a large language model developed by the American firm Anthropic.

Contents

> *"While anthropologists will find reasons to dispute Kenya's claim to being the cradle of humanity, its claim as the cradle of fintech is hard to challenge."*
>
> — Patrick Njoroge, Governor of the Central Bank of Kenya from 2015 to 2023

1 Introduction

Today almost 80% of the global adult population have access to a financial account, compared to merely half in 2011 (Klapper et al., 2025). This surge in financial inclusion over the past fifteen years is largely attributable to the immense growth of Mobile Money in developing countries (Klapper et al., 2025). Kenya represents one of the most prominent examples of this transformation with the introduction of M-PESA in 2007, often cited as the pioneering mobile financial services platform (Suri, 2021).

The widespread adoption of M-PESA enabled the rise of digital credit, which is typically defined as the remote, automated and instant provision of small micro-credit with a short repayment horizon (Chen & Mazer, 2016; Gwer et al., 2019; Suri, 2021; Upadhyaya et al., 2024). The digital nature drastically decreases transaction costs associated with the provision of microcredit. These products promise to overcome traditional barriers to credit access by eliminating collateral requirements and reducing administrative costs. As a result, more than a third of the Kenyan population has adopted digital credit, primarily through mobile banks, with hundreds of non-bank digital credit providers having entered to compete in the market (FinAccess, 2024; Wamalwa et al., 2019).

Despite the rapid diffusion of digital credit, evidence on its welfare effects remains limited. Past studies on traditional microcredit serve as a cautionary tale for its digital twin, as researchers often fail to observe its promised transformative effects. This is typically attributed to small average loan sizes hindering productivity-enhancing investments (Banerjee et al., 2015; Meager, 2019). Nevertheless, digital credit differs significantly in its digital appraisal and disbursement processes. These novel features prompt the need to investigate potential benefits and risks associated with digital lending.

Furthermore, in the late 2010s, several actors raised concerns about market misconduct among digital lenders in Kenya. The critique was concentrated on opaque and extortionate loan terms, high default rates and unethical debt-collection methods (Gwer et al., 2019; Wamalwa et al., 2019; Ngugi, 2020; Kimeu, 2022). In response to mounting evidence of consumer harm, the

Central Bank of Kenya launched a regulatory effort culminating in the (Digital Credit Providers) Regulations of 2022. The legislation brought digital lenders under the supervision of the Central Bank through the introduction of a licensing requirement, demanding *inter alia* compliance with consumer protection standards. This regulatory intervention raises additional questions on digital credit's potential impact on borrower outcomes and market dynamics.

This thesis explores the role of digital credit in the Kenyan financial landscape, its welfare implications on borrowers, and the Central Bank's regulations' potential impact on their financial health. Household survey analysis applying a propensity-scored difference-in-differences method is combined with qualitative fieldwork conducted in Nairobi to capture both measurable outcomes and institutional mechanisms underlying borrowing behaviour and market practices. Thus, this research addresses three questions: First, what role does digital credit play in the financial lives of Kenyan borrowers? Second, how does access to digital credit affect borrowers' financial well-being? Third, how has the recent regulatory framework (the Central Bank's digital credit regulation) affected borrowers' financial health and lenders' conduct?

Our findings suggest that digital credit primarily functions as a short-term liquidity instrument in response to structural economic vulnerability. Borrowers commonly use digital loans to finance emergency expenditures and smooth household consumption. However, welfare effects are highly heterogeneous. Borrowers with relatively stable incomes appear able to use digital credit productively, enabling the management of temporary liquidity constraints, whereas individuals with volatile incomes face a higher risk of debt cycling and over-indebtedness. This dynamic is important to acknowledge as households with volatile incomes constitute the majority of the Kenyan population. Furthermore, digital credit should, in theory, provide a welfare-enhancing consumption-smoothing mechanism for these households. This result illustrates the difficulty in effectively handling digital credit within the current Kenyan landscape, which is linked to a fundamental disconnect between loan terms and the average borrower's cash flows.

Quantitative survey analysis indicates that recent regulatory reform have had limited measurable effects on borrower behaviour in the short term. While modest reductions in debt distress are observed, the overall impact of regulation on default rates, basic needs and financial resilience appears small and insignificant. Qualitative evidence suggests that these limited effects reflect both the challenges of regulating a rapidly expanding digital lending sector and the persistent demand for short-term liquidity among financially vulnerable households.

By combining quantitative and qualitative evidence, this study contributes to the growing literature on digital financial services in developing economies. It provides new insights into the institutional environment surrounding digital lending, the behavioural dynamics shaping borrower decisions, the efficacy of a licensing-based digital credit regulation, and the heterogeneous welfare effects of digital credit.

This paper proceeds as follows: first a literature review and an introduction to the study setting surrounding digital credit in Kenya. Then data, settings and methodology are described in Section 2. Section 3 covers quantitative and qualitative results of our research. These are discussed in Section 4 whereas conclusions are provided in Section 5.

1.1 Literature review

This study stands at the intersection of three bodies of literature: research on financial inclusion and credit market development, the welfare effects of microcredit and digital lending, and the regulation of digital credit. Each part refers to a dimension of the research questions posed in this paper.

Financial inclusion and the role of credit market development

The historical exclusion of low-income populations from the credit sector is typically explained by information asymmetries between lenders and borrowers. Difficulty in gauging creditworthiness, coupled to adverse selection and moral hazard issues, makes credit rationing the rational choice among banks (Stiglitz & Weiss, 1981). Theory also suggests that consequent credit market imperfections, i.e., borrowing constraints, contribute to occupational segmentation which perpetuates poverty and income inequality, limiting productive investments and therefore stifling broader economic growth (Banerjee & Newman, 1993; Galor & Zeira, 1993). Conversely, reducing credit-market frictions through financial development is found to disproportionately favour the poor (Beck et al., 2007a).

Empirical evidence supports this theory in a range of low-income settings. The establishment of rural bank branches in India increased savings and credit usage while reducing poverty (Burgess & Pande, 2005). In addition, providing bank accounts to rural self-employed women have proven to increase savings, productive investments and household consumption (Dupas & Robinson, 2013). Financial access also correlates positively with the degree of economic development, quality of physical infrastructure, the institutional environment, and creditor

rights while correlating negatively with the cost of contract enforcement (Beck et al., 2007b). In Kenya, the expansion of mobile money through the M-PESA payments platform has proven to reduce transaction costs while enabling consumption smoothing by enabling risk sharing across households (Jack & Suri, 2014). These findings establish that extending access to formal financial services can meaningfully improve welfare, yet bank branches and payments differ significantly from digital credit, being short-term and high-cost by nature. This motivates our first research question: what role does digital credit play in the financial lives of Kenyan borrowers?

Welfare effects of microcredit and digital lending

The literature on microcredit serves as an important reference point when evaluating digital credit. The once hailed development programs focusing on the provision of microcredit to marginalized groups, aiming to unlock economic development and growth, have received increasing skepticism among development economics scholars. Instead of being transformative, empirical evidence finds them at best modest and heterogeneous. Across seven randomized evaluations of micro-credit interventions, no transformative effects were identified on household income or consumption (Banerjee et al., 2015). Similarly, a Bayesian hierarchical analysis confirms that average effects are small and variable across contexts (Meager, 2019).

More recent research question whether the lack of microcredit's transformative effects may be attributed to the small loan sizes hindering investments in productive assets, coherent with research on poverty traps (Nelson, 1956; Galor & Zeira, 1993; Banerjee & Newman, 1993). For instance, Balboni et al. (2022) tested for the existence of a poverty trap threshold when conducting a randomized transfer of a productive asset (in the shape of a cow) to 6000 rural Bangladeshi households living in extreme poverty. Their findings indicate a threshold level of initial assets needed to accumulate more assets, take on better occupations, and grow out of poverty (Balboni et al., 2022). Hence, the authors reinforced the argument that larger transfers which allow for the productive use of credit might be required for substantial welfare-improving effects. Moreover, evidence from a field experiment in Pakistan suggests that bigger loans, i.e., four times the typical borrowing limit for microcredit clients, have a greater positive impact on firm profits and household consumption than smaller ones (Bari et al., 2024). These findings are relevant to digital credit by illuminating how loan attributes, such as loan size, may influence digital lending outcomes.

Digital credit nevertheless differs from traditional microcredit, particularly in terms of lower transaction costs derived from its remote, automated and instant nature. Digital credit provision itself is a somewhat novel phenomenon and hence the current literature on its effects is scarce and mixed (Robinson et al., 2022). Several studies provide evidence that digital credit brings increased borrowing opportunities among those without historical access to credit in sub-Saharan Africa (McKee et al., 2015; Johnen et al., 2021; Tampuri, 2023). Notably, evidence from a study on the take-up and impact of a bank-backed digital credit product, M-Shwari, suggests that usage improves household resilience (Suri et al., 2021). In the study, households primarily reported having spent the loan on health emergencies, yet the authors also found that households' propensity to spend on education was related to digital loan usage (Suri et al., 2021). In addition, theory supports that access to loans with minimal transaction costs should have real welfare benefits (Robinson et al., 2022).

While some research points towards the existence of welfare-enhancing effects, it should not be interpreted as conclusive evidence. For instance, another study on digital credit in Malawi, on a product called Kutchova, found little impact on loan takers' well-being (Brailovskaya et al., 2024). The authors primarily attribute the limited welfare gains to the small average loan size, equivalent to a few dollars, and hidden fees in the loan terms, leading to high additional borrowing costs (Brailovskaya et al., 2024). Further, the high demand for digital credit coupled with low financial literacy and limited consumer awareness of loan terms generates conducive conditions for predatory behavior among lenders (Brailovskaya et al., 2024). The speed of delivery is also found to be a contributing factor to the high default rates (Burlando et al., 2023). Moreover, digital borrowing was also responsible for 90% of all blacklistings in Kenya, related to high default and report rates, potentially decreasing long-term financial access (Johnen et al., 2021). Others report on issues of fraud, non-transparent fees, over-indebtedness and violations of consumer, data and privacy protection (McKee et al., 2015; Tampuri, 2023). Thus, current literature point towards heterogenous welfare effects which are dependent on borrower characteristics and lender conduct. However, the mechanisms underlying this heterogeneity, namely the institutional environment shaping borrowing behaviour and outcomes, is yet to be thoroughly studied. This motivates our second research question: how does access to digital credit affect borrowers' financial well-being?

Regulation of digital credit markets

The documented risks associated with digital lending have prompted calls for stronger regulatory oversight of the sector (Tampuri, 2023; Brailovskaya et al., 2024). In Kenya, the late 2010s brought mounting evidence of market misconduct, concentrated around opaque loan terms, high default rates and aggressive debt collection practices, which ultimately prompted the Central Bank to introduce a licensing framework through the Digital Credit Provider Regulations of 2022 (Gwer et al., 2019; Wamalwa et al., 2019; Ngugi, 2020; Kimeu, 2022).

A small yet growing literature has begun to examine the digital credit regulation in Kenya. For example, Upadhyaya et al. (2025) argue that the regulation of digital credit in Kenya is characterized by the government's market-led ideology while highlighting the structural power of Kenyan banks and the mobile network operator Safaricom, as they constitute critical infrastructure and generate substantial tax revenues. Findings from another study suggest that the Central Bank of Kenya Amendment Bill 2021 lacks sufficient provisions on excessive interest rates, data protection and complaints channels (Kim & Duvendack, 2025). These studies are valuable in framing the institutional context, yet neither cover the most recent and comprehensive regulation, The Central Bank of Kenya (Digital Credit Provider) Regulations 2022, nor provides empirical evidence on its impact on borrower outcomes.

Kenya is the relevant and chosen context for our study as it is a protagonist and frontrunner for digital financial services among developing countries. There are nonetheless rapidly scaling credit sectors in other developing countries both in sub-Saharan Africa and beyond who are facing questions on how to design their regulatory efforts. Thus, we attempt to fill a significant research gap on what a licensing-based regulatory intervention may achieve in terms of borrower welfare. This motivates our third research question: to what extent has the recent regulatory framework influenced borrower outcomes and market conduct?

1.2 Study setting

A comprehensive definition of digital credit regard the remote, automated and instant provision of small micro-credit, typically with a short repayment horizon where the loan disbursement and repayment occur through a mobile money account (Chen & Mazer, 2016; Gwer et al., 2019; Upadhyaya et al., 2024). The remote and automated process is enabled by the digital credit providers processing of digital data, e.g. internal subscription or transaction data from the mobile network operators alongside personal data such as social media presence, to determine

loan eligibility and credit-worthiness (Hwang & Tellez, 2016). In addition, they compensate for the innate higher risk character of the loans by having smaller average loan sizes, higher interest rates and shorter repayment horizons compared to traditional credit (Gwer et al., 2019). For instance, the typical loan size range from 7 USD to 50 USD (Hwang & Tellez, 2016). The typical repayment duration from one week to a month with percentage rates spanning from 5% to 40% on a monthly basis, corresponding to annual percentage rates from 60% to 480% (Gwer et al., 2019).

The majority of digital credit is disbursed by what is referred to as 'mobile banks', who are estimated to control 80% of the market (Upadhyaya et al., 2025). Mobile banks are collaborations between mobile network operators and banks, where the service is offered on the mobile network operator's digital platform (i.e., app or website) yet accounted for on the bank's balance sheet. Officially recognized as a bank product, they are regulated by the Bank Act (2006) and supervised by the Central Bank's Bank Supervision department (CBK, 2006). Related to these mobile banks are their overdraft facilities, with Fuliza, the product introduced by Safaricom, NCBA and KCB in 2019 being the first and most known. The Fuliza product allows customers to make payments which exceed their available funds on their mobile money accounts (M-PESA). The sole requirement is to be a registered M-PESA customer, and you are given a Fuliza M-PESA limit based on your Safaricom usage, such as your subscription. Importantly, Fuliza has a 'sweep' function, where funds which are remitted to an M-PESA with an unpaid Fuliza overdraft facility is immediately deducted from the transfer.

The most common type of digital credit provider is the digital lender. A digital lender operates through mobile applications which can be downloaded through online software stores, such as Apple's App Store and Google's Play Store. The primary difference from the mobile banks is that they are not allowed to let customers deposit and save money. Instead, they use their raised funds, e.g., equity and debt capital, to solely disburse digital credit. As such, they initially fell between the sector-specific regulations of deposit-taking financial institutions in Kenya, including the commercial banks, microfinance banks and SACCOs (Gwer et al., 2019). Another key difference is also the lesser degree of collaboration with Safaricom, where digital lenders typically are not able to access its proprietary transactional and usage data. Therefore, these kinds of providers rely to a larger extent on alternative data in their credit scoring algorithms. For instance, the digital lenders have historically collected data on phone usage, including messages and emails, physical address, social media accounts, economic status, income range,

gender and guarantor (Gwer et al., 2019). Still, the digital lenders also utilize the credit reference bureaus' credit information (if any) and their internal customer credit histories alongside the alternative data. Digital lenders are the subjects of our study.

The primary regulator of digital lenders is the Central Bank of Kenya, which oversees their operations through the licensing put forward in the Central Bank of Kenya (Digital Credit Provider) Regulations 2022. The Regulations implemented the licensing provisions put forward in the Central Bank Amendment Act (2021) and thus stipulates the licensing requirements. These include, yet are not limited to, extensive descriptions of utilised technology, pre-defined operations, terms and conditions, pricing model, credit policy, anti-money laundering and illicit financing policy, data protection policy, corporate governance policy, consumer complaints channels and mechanisms, proof of legal sources of funds, credit bureau reports and 'fit and proper' criteria among senior managers and shareholders (CBK, 2022). This regulation is the foundation for the quantitative analysis.

2 Materials and methods

This study adopts a mixed-methods design, combining quantitative survey analysis with qualitative fieldwork. The choice of this approach reflects both the nature of the research questions and the limitations inherent to each method individually.

The three research questions pursued in this paper operate at different levels of analysis. The second and third questions, concerning the welfare effects of digital credit and the impact of the 2022 regulations, lend themselves to quantitative measurement, insofar as household survey data can capture changes in financial outcomes across a population. However, the first question, what role digital credit plays in the financial lives of Kenyan borrowers, is fundamentally concerned with mechanisms, motivations and institutional context, which aggregate survey data is poorly equipped to illuminate. Even for the second and third questions, quantitative analysis alone cannot account for why patterns emerge: it can compute effects of the regulations, but fails alone to explain through which channels the mechanisms of these outcomes occur. The effect may, for instance, capture compliance to the new regulation, a change in lender conduct or a shift in borrower behaviour. Qualitative fieldwork is therefore necessary for meaningful interpretation of the quantitative results.

This position finds support in the broader methodological literature. Starr (2014) identifies several conditions under which qualitative or mixed-methods research is superior to purely quantitative approaches: when the field of inquiry is novel and exploratory, when quantitative methods alone cannot resolve the questions at hand, when the subject of study is complex and contextually embedded, and when the perspectives of the economic agents under study are intrinsically valuable. We argue that all four conditions apply in this research. First, digital credit regulation is a recent and rapidly evolving phenomenon with limited empirical precedent. Second, our quantitative strategy, as outlined below, faces identification challenges that qualitative evidence can partially address. Third, the institutional environment surrounding digital lending in Kenya is shaped by intersecting regulatory, commercial and social forces where survey analysis alone would generate a reductive interpretation. Fourth, the lived experiences of borrowers, their motivations, constraints and perceptions, constitute an important object of inquiry in themselves, not merely a means of verifying aggregate results. Cartwright & Igudia (2024) make a similar argument for the social sciences more broadly, contending that mixed-methods research is particularly well-suited to understanding the informal and contextually specific dimensions of economic behaviour that quantitative models tend to abstract away.

Thus, we aim to demonstrate the usefulness of a mixed-methods approach within development economics with this thesis.

The two methodological parts are designed to complement one another in a specific way. The quantitative analysis estimates the aggregate effect of the 2022 Digital Credit Provider Regulations on borrower outcomes using household survey data from the FinAccess surveys. Where this analysis identifies effects, or, as it turns out, the absence of substantial effects, the qualitative part provides the institutional and behavioural evidence needed to interpret them. Where the quantitative analysis faces binding identification constraints, the qualitative evidence offers an independent line of reasoning grounded in the accounts of borrowers, lenders, regulators and sector experts. The two parts thus speak to one another throughout the analysis, and their integration is the central analytical contribution of the mixed-methods design.

The remainder of this section describes the data sources for each part, the construction of key variables, and the empirical strategy applied in the quantitative analysis.

2.1 Data

Survey data

The quantitative part of the thesis builds on data from the FinAccess Household surveys, which are produced by the Kenya National Bureau of Statistics in collaboration with the Central Bank of Kenya and Financial Sector Deepening Kenya. The surveys measure financial access and inclusion in Kenya from a consumer perspective. The data is collected through computer-assisted face-to-face interviews (FinAccess, 2016, 2019, 2021, 2024).

The FinAccess surveys are conducted almost every third year since 2006. We utilize the surveys from 2016 onwards, as it was the first year to include questions regarding digital app loans. Consequently, our dataset includes the following survey waves: 2016, 2019, 2021, and 2024. These were then merged into a single dataset. Thus, our dataset contains repeated cross-sectional data which allows us to estimate aggregate effects.

The sample design for the 2016 and 2019 data collection is drawn from the fifth National Sample Survey and Evaluation Programme (NASSEP V) household sampling frame, which utilizes the 2009 Kenya Population and Housing Census (FinAccess, 2016, 2019). The sampling method was then updated for the remaining years as the Kenyan Household Master Sample Frame (K-HMSF) was introduced in concurrence with the 2019 Kenya Population and Housing Census (KPHC)

data (FinAccess, 2021, 2024). All years have been weighted to ensure they are representative on a national level and to account for non-responses. Furthermore, the 2021 and 2024 survey waves are representative at the county level, while the 2016 and 2019 survey waves are representative on a regional level (FinAccess, 2016, 2019, 2021, 2024). Concerning the questionnaire design, there are some differences between each survey wave in the content of questions and how some questions have been framed. To ensure that we have sufficient variables in our dataset, we have allowed for some differences in the framing of questions, where some variables are built on multiple-choice questions in one survey wave and not in another year.

Qualitative data

The primary source of qualitative data are semi-structured interviews with digital credit stakeholders in Kenya. The following stakeholder groups were defined as key: digital lenders, borrowers, regulators, credit reference bureaus, researchers and financial inclusion experts.

A snowball sampling strategy (Moser & Korstjens, 2018) was applied to recruit the majority of stakeholder interviewees, including the policy experts, digital lenders and regulators. After having recognized the prevalence of digital borrowing among Uber drivers, convenience and criterion sampling were combined to include them in the sample. The following method was applied: each Uber driver, in a ride lasting longer than 15 minutes, would, after building rapport through standard greetings and phrases, be asked to participate in an interview if they had ever taken a digital app loan themselves. A total of nine interviews were held using this method. Lastly, purposive sampling was applied when attempting to gauge the perspectives on digital credit by some of the most vulnerable and undocumented individuals, namely residents in the Kibera slum. This was implemented through a field-visit with a local guide and resulted in three interviews. In total, the abovementioned sampling strategy yielded a total of 28 interviews held from October to December 2025.

Furthermore, two focus group sessions were held in December of 2025. The first consisted of nine women principally working as nannies or housekeepers. The second had six participants, consisting primarily of men working as gardeners and guards. Both groups of domestic workers supplied their labour in the affluent neighbourhood of Rosslyn, Nairobi. An anonymized list of participants in the qualitative study is provided in the appendix.

2.2 Variables

The FinAccess Household surveys encompass various aspects related to the respondents, such as data on demographics, financial well-being, and economic behaviour. The primary questions of interest for our research are those associated with the usage of digital app loans, as our treatment assignment is based on them. In each survey wave, respondents were asked if they are currently using, have used, or have never taken a loan through a phone that you download on an app, in other words, a digital app loan. We exploit the respondents' answers to this question to construct the treatment assignment that builds on uptake in each county, approximated by share of current users and past users. A more detailed review of the construction of the treatment assignment is described in the empirical strategy.

The chosen outcome variables are related to respondents' financial health and indebtedness. Among these, the default rate on digital app loans are considered a key outcome variable, as it indicates repayment difficulties. The second primary outcome variable is debt distress. It is constructed as an index based on two variables indicating activities signaling debt distress: selling assets or borrowing to meet current debt obligations. The debt distress index is supposed to measure over indebtedness, therefore serving as an indicator of financial health. The third outcome variable is financial resilience, also constructed as an index. It is based on respondents' ability to access a lump sum of money, whether they set money aside for emergencies and if they have set outside money for other specific long-term purposes. The financial resilience index is included in the analysis as it measures the household's ability to cope with economic shocks, another aspect of financial health. The last main outcome variable measures respondents' basic needs. It is an index based on answers to questions on food security and access to medicine.[1] Similar to the other indexes, it is associated with financial health, but captures more severe day-to-day hardships.

2.3 Methodology

In this thesis, we adopt a mixed-method approach by combining a quantitative analysis with qualitative field interviews. The quantitative analysis is built on two parts: a propensity score model followed by a difference-in-differences design.

[1]Each index is constructed by computing the row mean of the binary variables included, resulting in a continuous measure from 0 to 1. High results for debt distress indicate more financial stress, while high score for financial resilience and basic needs indicate greater resilience and more fulfilled basic needs respectively.

Empirical Strategy

The treatment assignment in our paper is built on a proxy measure of exposure to the Central Bank of Kenya (Digital Credit Provider) Regulations 2022 across counties in Kenya. We approximate exposure to regulation through digital app loan uptake within counties, based on the hypothesis that the regulation should have a greater effect on counties with a larger degree of exposure. Since digital app loan usage fluctuates across counties over the years, we use digital app loan prevalence at the closest year before regulation (2021) as a base for treatment, to reflect counties' exposure at the time of the regulation[2]. Then, heterogeneity in average digital app loan uptake among counties in 2021 is exploited to construct a binary treatment. The treatment assignment threshold is based on the distribution of average digital app loan usage across the counties. As depicted in Figure 9 in the appendix, the distribution is multi-modal. We exploit one of the lower modes as it serves as a natural threshold, following a strategy for deciding treatment status applied in previous research (see Curtis et al., 2022; Bannert et al., 2023). Given the existence of multiple lower modes, the one closest to median is used (0.04). This follows the standard threshold choice for binary treatment assignment in difference-in-differences designs (see, e.g., Kelishomi & Nisticò, 2024; Jurek, 2023).

Propensity score model

An issue with the treatment assignment is that the counties were not randomly selected to have high or low exposure to the intervention, resulting in a non-random treatment assignment. Consequently, high-exposure counties may differ in certain characteristics from low-exposure counties, with endogeneity potentially confounding the estimated treatment effect. Several papers have illuminated that propensity score models are effective in eliminating systematic differences in baseline characteristics between treated and untreated units (Austin, 2011). The propensity score model predicts treatment assignment, given a set of observable baseline characteristics. We apply an inverse probability weighting model where the estimated propensity scores are used to construct weights to create a synthetic sample in which the distribution of measured baseline covariates is independent of treatment assignment. The applied method was chosen to preserve the entire sample, given the low initial sample size.

There is limited consensus regarding the variables to include in a propensity score model (Austin, 2011). However, the standard recommendation is that covariates should affect treatment

[2]A Pearson correlation test, reported in Table 3 in the appendix, shows that county-level usage is not perfectly correlated across survey waves, justifying the use of the 2021 measure as a baseline for treatment.

assignment and outcome variables simultaneously, excluding such variables would otherwise lead to confounding results (Caliendo & Kopeinig, 2005). Following this criteria, we have included the following variables: residence, education level, internet access, and mobile ownership. Financial inclusion varies with both residence and education level, where informal lending practices are more commonly used in rural areas and among less educated individuals (FinAccess, 2024). Therefore, it is plausible to assume that residence and education level influence both our treatment assignment and financial health outcomes. Access to internet and a mobile phone are prerequisites for downloading the app through which you can access digital app loans, and can serve as good predictors of the treatment assignment. Both enables participation in the broader economy, increasing the exposure to multiple digital credit platforms, in turn raising the likelihood of accessing credit and experiencing debt distress.

Another criterion in relation to the model specification is that the covariates remain unaffected by the treatment or any anticipation of it. To address these issues, one can use the years before the intervention as a matching baseline (Caliendo & Kopeinig, 2005). Therefore, our model specification only includes 2016, 2019, and 2021, all prior to the implementation of the regulation. Concerning the risk of any anticipation effect, all the included covariates represent relatively stable socioeconomic characteristics that are unlikely to change in response to the anticipation of the regulation. Table 4 in the appendix reports the covariate balance with and without the inverse probability weighting.

Lastly, the model specification relies on the 'common support' assumption, which states that there should be an overlap between characteristics between treated and untreated units. It rules out the possibility of perfect predictability of treatment assignment to ensure that all units have a positive probability of being treated or untreated, which is required for valid inverse probability weights (Austin, 2011). To ensure that this condition holds, a graph over the propensity score distribution among our control and treated samples is depicted in Figure 10 in the appendix, which shows that this condition is indeed satisfied.

Difference-in-differences model

A difference-in-difference regression with county and year fixed effects is utilized to estimate the treatment effect. The county fixed effects control for time-invariant differences in characteristics across counties, mitigating any unobserved heterogeneity in characteristics between the treatment and control groups that remains after the propensity score matching model has been applied.

The year fixed effects controls for any potential shocks that occurred during the years across all the counties. Furthermore, the regression controls for income sources. The following types of income sources are included: farming, employment, casual work, business, and being dependent on friends or family members for financial support. Though main income source may seem rather stable across years, this is not the case for Kenya. Farming has become less reliable due to poor weather conditions, forcing people to change occupation (FinAccess, 2024). As occupational changes may change over time and across counties, they are not absorbed by the time or unit fixed effects, therefore included as controls. To mitigate potential heteroskedasticity and serial correlation issues, clustering is performed on a county level, the same level as the treatment assignment. Below follows the regression specification along with a brief explanation of each variable included.

$$Y_{ict} = \alpha_c + \lambda_t + \delta(\text{Post}_t \times \text{Treat}_{c,\text{pre}}) + \beta' X_{ict} + \varepsilon_{it} \tag{1}$$

where:

- Y_{ict} is the outcome variable for individual i in county c at time t.
- α_c is the county-level fixed effect, which controls for time-invariant differences in characteristics between counties.
- λ_t is the time fixed effect that controls for potential shocks that could affect all the counties.
- δ represents the interaction between the treatment and the year variable, capturing the effect of being both treated and after the treatment, i.e., the treatment effect.
- Post_t is a dummy variable that indicates whether it is before or after the regulation.
- $\text{Treat}_{c,\text{pre}}$ is a dummy that captures whether the county is treated or not.
- β' captures the set of coefficients associated with the controls.
- X_{ict} entails the set of controls in the regression.
- ε_{it} is the error term.

The difference-in-differences framework with fixed effects relies on several identifying assumptions. The first is the parallel trends assumption, stipulating that in the absence of the treatment, treated and control counties would have followed similar trends (Callaway and Sant'Anna, 2021). The second assumption is the 'no anticipation' condition, which requires that the counties with high exposure to the regulation (treated counties) do not adjust their behavior to the regulation before its implementation (Malani and Reif, 2015). We examine whether these assumptions holds through a set of diagnostic checks presented along with their results, in the quantitative results section.

2.3.1 Qualitative data analysis

The interviews and focus group sessions were recorded and transcribed. The transcriptions were thereafter read and inductively coded (Moser & Korstjens, 2018). A total of 805 individual excerpts were assigned a primary and a secondary code. The primary code was intentionally broader, with examples including 'borrower experience' and 'regulatory trigger'. Examples of corresponding secondary codes include 'debt cycling' and 'consumer harm'. These codes were then assigned into 40 categories, often corresponding to the primary codes' abstraction level: e.g., 'regulatory ideology', 'market dynamics' and 'repayment behaviour'. These categories were then transformed into five overarching themes: Institutions and demand, market structure and incentives, digital credit characteristics, borrower experience and impact. These themes were later synthesized into the eight sections constituting the qualitative results section.

3 Results

3.1 Quantitative results

Table 1 presents the IPW (inverse propensity score weight) fixed effects difference-in-differences regression estimates with and without controls for each dependent variable: digital app loan defaults, debt distress index, financial resilience index and the basic needs index.

Table 1: Difference in Difference Estimates

	Digital app defaults		Debt distress		Financial resilience		Basic needs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No controls	With controls	No controls	With controls	No controls	With controls	No controls	With controls
Treatment × Post	0.002	0.002	-0.094***	-0.091***	-0.004	-0.009	0.013	0.009
	(0.004)	(0.004)	(0.023)	(0.022)	(0.026)	(0.025)	(0.026)	(0.025)
Employed		0.012***		-0.012		0.213***		0.145***
		(0.002)		(0.015)		(0.016)		(0.024)
Farming		0.005**		0.082***		0.070***		-0.007
		(0.002)		(0.010)		(0.013)		(0.020)
Casual Worker		0.009***		0.052***		-0.034*		-0.085***
		(0.003)		(0.011)		(0.018)		(0.020)
Business Owner		0.015***		0.058***		0.129***		0.061***
		(0.003)		(0.010)		(0.017)		(0.019)
Money Support		0.005		0.031*		-0.051***		0.045**
		(0.003)		(0.016)		(0.015)		(0.018)
Constant	0.011***	0.003	0.207***	0.160***	0.359***	0.311***	0.607***	0.595***
	(0.001)	(0.002)	(0.004)	(0.011)	(0.004)	(0.015)	(0.004)	(0.018)
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47742.000	47742.000	37124.000	37124.000	55722.000	55722.000	55722.000	55722.000
R-squared	0.003	0.004	0.048	0.057	0.075	0.145	0.147	0.177
Clusters	47.000	47.000	47.000	47.000	47.000	47.000	47.000	47.000

Notes: County and year fixed effects included. Standard errors (in parentheses) are clustered at the county level. Weights: individual sampling weight × inverse probability weight (IPW). * p<0.10, ** p<0.05, *** p<0.01.

3.1.1 Debt distress

The fixed effects difference-in-differences estimates for the outcome variable debt distress presents negative coefficients of 9.4% (without controls) and 9.1% (with controls), both statistically significant at a 1 percent level (see Table 1).

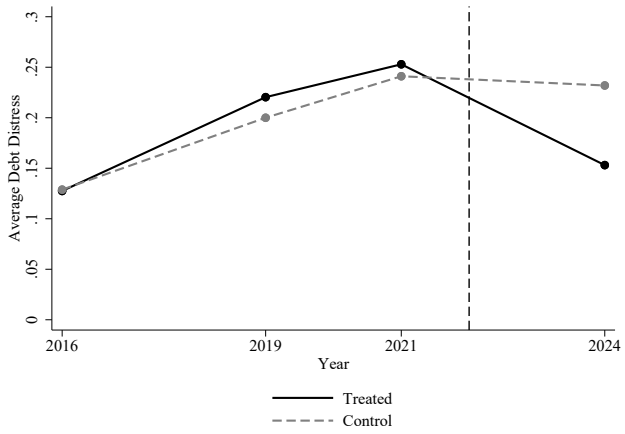

Figure 1: Average debt distress across years

Source: Author's rendering of FinAccess data (2016, 2019, 2021, 2024).

Figure 1 depicts the IPW-weighted debt distress index mean for the high exposure counties and low exposed counties across the year 2016 to 2024. Prior to the regulation debt distress is rising among both treated and control counties. When the regulation is introduced the debt distress slightly falls. Figure 1 shows that the fall is more pronounced for the high exposure counties.

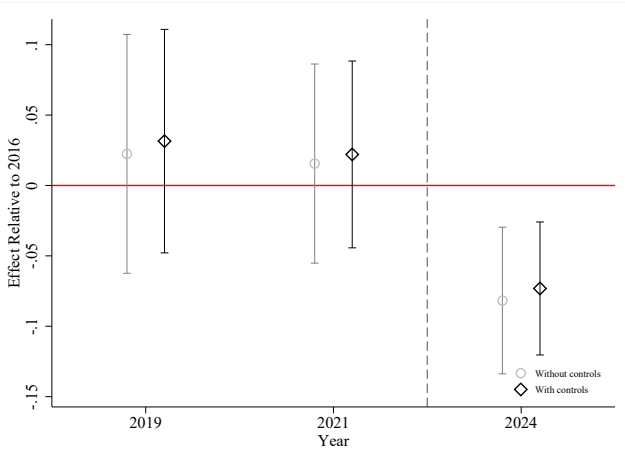

Figure 2: Event study: Debt distress

Figure 2 depicts an event-study plot, showcasing the dynamic effects of the regulation on debt distress, using 2016 as baseline for each year. The figure presents year estimates with and without controls for 2019, 2021 and 2024, with 95% confidence intervals. The years before the intervention are indistinguishable from zero, which strengthens the comparability between high and low exposure counties. The 2024 negative estimates are statistically distinguishable from zero, implying that the regulation reduced debt distress among high exposure counties.

The findings from Table 1 indicate that the regulation is associated with a decline in debt distress among high-exposure counties. Low and high exposure counties exhibits similar trajectories prior to the regulation, as shown in Figure 1 and in Figure 2, this implies that the parallel trend is supported here. Furthermore, as outcomes in high-exposure counties do not diverge from the control group prior to the regulation, there is no anticipation effect.

3.1.2 Digital app loan default

Digital app loan default exhibited a small increase of 0.2% both with and without controls, neither being statistically significant (see Table 1).

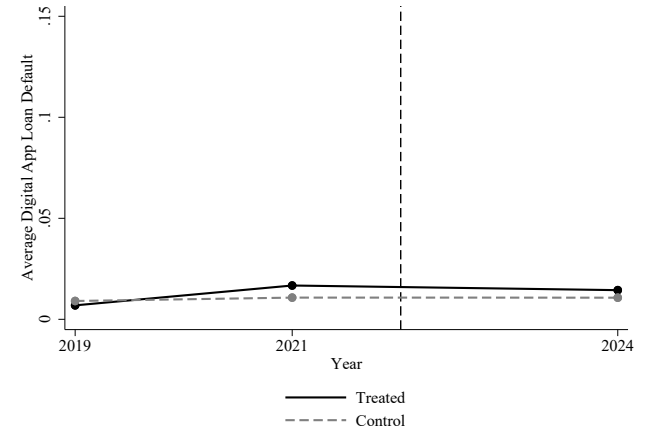

Figure 3: Average digital app loan defaults across years

Source: Author's rendering of FinAccess data (2019, 2021, 2024).

Figure 3 depicts the trend of the IPW weighted average digital app loan defaults across years, among the high exposure (treated) counties and low exposure (control) counties. High exposure counties exhibit a small increase in average defaults before the regulation, while the low exposure counties curve is flat across all years. As the regulation is introduced we observe that average defaults fall somewhat for the high exposure counties. Although small disparities in the trends prior to and after the introduction of the regulation exist, these differences are negligible in magnitude and do not suggest a systematic divergence prior to the regulation, implying that the parallel trend- and no anticipation condition holds here.

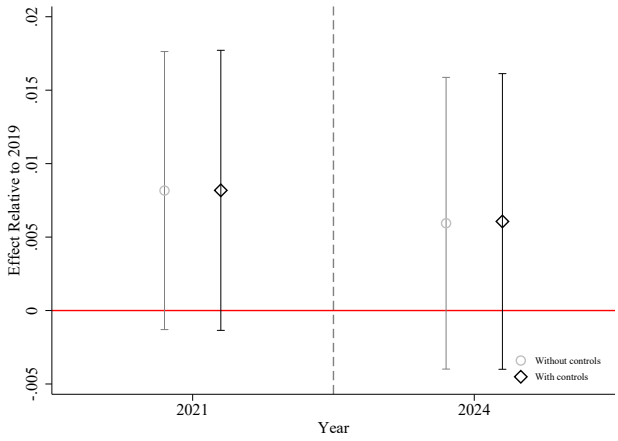

Figure 4: Event study: Digital app loan default

Figure 4 displays a dynamic event-study plot with year by year estimates with and without controls on digital app loan default with 95% confidence intervals, using 2019 as baseline for each year. The estimate prior to the intervention is indistinguishable from zero, indicating that the pre-trends, although short, are parallel before the regulation. The event study estimates for 2024 are indistinguishable from zero, indicating that the introduction of the regulation had no effect on the digital app loans default rates, consistent with the results from Table 1.

3.1.3 Financial resilience

The outcome variable financial resilience presents a small estimated negative coefficients of 0.4% (without controls) and 0.9% (with controls), as presented in Table 1. None of the results are statistically significant.

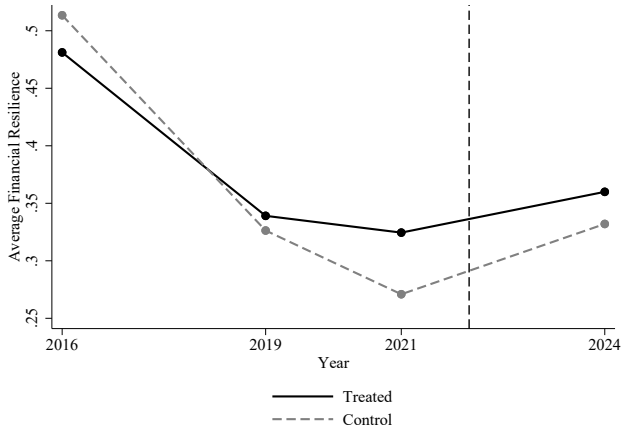

Figure 5: Average financial resilience across years

Source: Author's rendering of FinAccess data (2016, 2019, 2021, 2024).

Figure 5 entails a plot of the IPW weighted mean financial resilience for high- and low exposure counties between 2016 and 2024. Both groups broadly follow similar trajectories prior to the intervention, although the trend is flatter for the high exposure counties. Prior to the regulation both groups' mean financial resilience drops, but the slope is slightly steeper for the control group. During the implementation of the regulation, from 2021 to 2024, both groups exhibit a recovery in financial resilience, though the low exposure counties exhibit a more pronounced recovery.

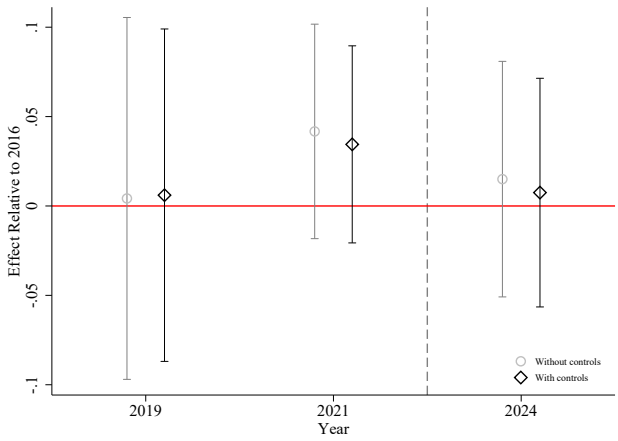

Figure 6: Event study: Financial resilience

Figure 6 conveys dynamic event-study estimates with 2016 as baseline. The figure entails estimates with a 95% confidence interval for years 2019, 2021 and 2024, with and without controls. All estimates are statistically indistinguishable from zero.

The findings from Table 1 together with the depicted trends in Figure 5 indicates that the regulation had little effect on financial resilience among the highly exposed counties. The flatter trend among high exposed counties illustrated in Figure 5 raises concerns if the parallel trend assumption holds, as it showcases that the financial resilience is more stable for the high exposed group across all years, and the divergence between groups becomes somewhat more pronounced closer to the regulation, suggesting anticipatory behavior. However, the estimated differences shown in Figure 6 are indistinguishable from zero in all pre-treatment years. This provides reassurance that the parallel trends and no-anticipation assumptions are not violated, though the imperfect pre-treatment trends should be acknowledged as a limitation.

3.1.4 Basic needs

The fixed effects difference-in-differences regression estimates for the basic needs outcome variable, presented in Table 1, are positive and statistically insignificant coefficients of 1.3% (without controls) and 0.9% (with controls).

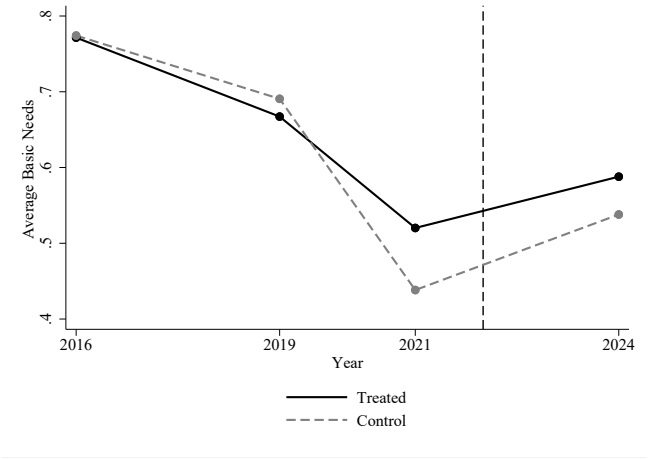

Figure 7: Average basic needs across years

Source: Author's rendering of FinAccess data (2016, 2019, 2021, 2024).

Figure 7 depicts the IPW weighted mean of the basic needs outcome variable between 2016 and 2024, for treatment and control group. Both groups followed roughly similar trajectories throughout the period. There is a downward trend between 2016 and 2021 (pre-regulation), followed by an upward trend from 2021 to 2024. Although both groups exhibit similar trends across the years, the treated group exhibits a flatter decline during 2019–2021, while the control group experiences a more pronounced drop. The subsequent upward trends are similar across the groups, though control groups experience a somewhat steeper upward trend.

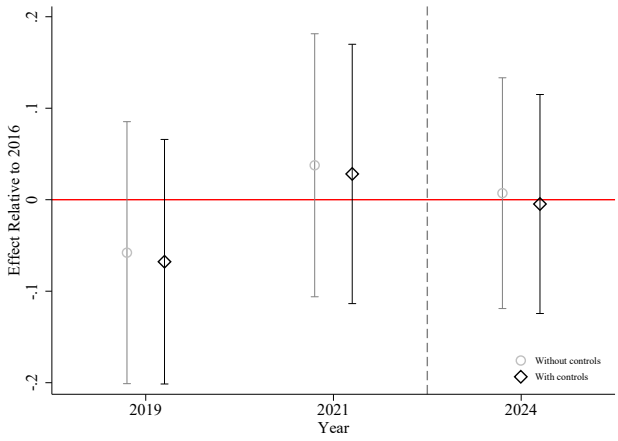

Figure 8: Event study: Basic needs

Figure 8 displays the dynamic event-study estimates, with a 95% confidence interval, using 2016 as baseline year. None of the coefficients before 2022 are statistically different from zero. The post-treatment estimates are close to zero, consistent with the DiD estimates presented in Table 1.

The findings from Table 1 suggest that high exposure to the regulation is associated with a small yet statistically insignificant increase in basic needs. Furthermore, the disparities in pre-trends depicted in Figure 7 suggest that the DiD estimate might be affected by pre-existing divergence in trajectories before the regulation. The event study estimates showcase that there are some differences between control and treatment group in point estimates for the outcome variable, especially in the year closest to the regulation, potentially raising concerns of an anticipatory effect. However, as all results are statistically insignificant prior to the regulation as shown in Figure 8, this reduces the concerns related to the anticipation effect and parallel trend.

3.1.5 Robustness checks

To further corroborate the results from our quantitative analysis several robustness and sensitivity checks were conducted. They are presented in this section.

In the inverse probability weighting model we test the sensitivity of the model by changing weighting baseline years and adding covariates to the weighting model. Firstly, weighting was conducted by adding more covariates to the model. The differences in the estimates compared to the main results are small, as demonstrated in Table 8 in appendix. Secondly, weighting was conducted using 2021 as baseline year only, instead of all three years prior to the intervention.

The results are presented in Table 10 in appendix. While there are some small differences in the estimates compared to the main results, these are fairly consistent with the main results. These findings suggest that the main results are not driven by compositional bias arising from differences in sampling frames between survey waves, and are robust across alternative specifications of the inverse probability weighting model.

To further test whether the results are driven by compositional bias, the fixed effects difference-in-differences regressions are conducted using only data from the 2021 and 2024 survey waves, since prior years have different representativeness. Table 11 in the appendix presents the estimates of these regressions. Most of the results are consistent with the main findings using all three prior years. The estimates for debt distress exhibits a somewhat bigger effect compared to the main regression, but the significance and direction remain the same as in the main regression. The most notable difference is the estimate of financial resilience showing a significant negative effect when controls are included, which contrasts with the main result where the estimate was insignificant. While this suggests some sensitivity in the financial resilience estimate, the overall pattern of results remains broadly consistent with the main specification, and we do not consider compositional bias across survey waves to be a primary driver of our findings.

In addition to checking for compositional bias, we asses the robustness of our treatment design by using alternative treatment thresholds of 0.03 and 0.05, compared to 0.04 that we use as threshold in our main regression. The results are presented in table 12 and 13 in appendix. Both results are broadly consistent with our main results, in both direction and significance, only differing with small percentages, most notably in debt distress. Overall, the results suggest that our results are not sensitive to small change in treatment threshold, supporting the robustness of the treatment design.

To further assess whether the parallel trend assumption holds, a placebo test was conducted. The test showcases if the treatment effect is driven by pre-existing differences in trends rather than by the regulation. The placebo test uses 2020 as the treatment date instead of 2022. In Table 14 (in the appendix), the results of a regression using 2020 as treatment year are presented. The outcome variable basic needs exhibits positive coefficients that are significant. The debt distress estimates are negative and significant, implying that there may exist underlying trends affecting our main results, rather than regulation. The significant estimates may reflect prior heterogeneous shocks such as the COVID pandemic that potentially affected counties differently, and therefore cannot be fully absorbed by the year fixed effects. Taken together, these results

indicate that the parallel trend does not hold for basic needs and debt distress, raising concerns on the ability to pursue causal inference of our results. All other outcome variables remained insignificant here.

3.2 Qualitative results

The quantitative analysis presented above establishes that the 2022 Digital Credit Provider Regulations had limited measurable effects on borrower outcomes in the short term, with the partial exception of a modest reduction in debt distress among high-exposure counties. What it cannot establish is why. Aggregate survey estimates are silent on the institutional environment within which digital credit operates, the behavioural logic that drives borrowing decisions, the commercial incentives shaping lender conduct, or the mechanisms through which regulation does, and does not, translate into changed market behaviour. The qualitative analysis that follows addresses these questions directly, drawing on 28 semi-structured interviews and two focus group sessions conducted with digital credit stakeholders in Nairobi between October and December 2025.

The analysis pursues four interconnected analytical goals. The first is to understand the structural conditions that generate demand for digital credit in Kenya, that is, to situate borrowing behaviour within the broader economic and institutional context rather than treating it as an isolated financial decision. The second is to examine how the welfare effects of digital credit vary across borrower types, and to identify the mechanisms that determine whether a given borrower is likely to benefit from or be harmed by access to digital lending. The third is to assess the regulatory environment surrounding digital credit, including the ideological, institutional and operational factors that shaped both the design of the 2022 Regulations and the challenges encountered in their implementation. The fourth is to capture the perceptions of borrowers and industry actors toward digital lenders and the regulatory intervention, as these perceptions are informative in themselves and help explain patterns of behaviour that aggregate data cannot fully account for. Together, these goals are oriented toward providing the contextual depth needed to interpret the quantitative findings and to offer a richer account of the role of digital credit in contemporary Kenyan society than either method could achieve alone.

The qualitative results are organized into eight thematic sections, each corresponding to a major theme that emerged inductively from the coding process. They move from the structural drivers

of digital credit demand, through the heterogeneous welfare experiences of borrowers, to the institutional dynamics of the regulatory environment and its observed outcomes.

3.2.1 Digital credit as a response to structural vulnerability

Structural economic vulnerability emerged as a key driver of digital borrowing. Across interviews and focus groups, respondents consistently described irregular incomes and economic hardship. Many households rely on informal or unstable employment, frequently creating liquidity gaps between income and essential expenditures. As one borrower stressed: "Unless you get a good job, [...] it is very difficult to meet day-to-day expenses." (Interview 13) In addition, access to social security support is scarce among borrowers, where the acute and immediate financial needs tend to crowd out contributions to the national health insurance scheme (Interview 2). Thus, digital credit serves as a readily available coping mechanism for short-term liquidity issues. This illustrates how demand for digital credit is linked to existing economic precarity rather than an isolated borrowing decision.

This economic precarity is linked to a persistent exclusion from traditional credit, allowing digital lenders to generate financial inclusion. Credit is heavily rationed in Kenya as commercial banks have been unable (or unwilling) to underwrite loans to individuals without adequate credit histories or collateral. Consequently, respondents report a demand for credit significantly exceeding available funding sources and levels. Put distinctly by a financial policy expert: "Bank credit is still very minor. So, when these [digital] lenders were coming into the market, there was a real need that they were coming to fill." (Interview 2) The enduring credit access gap creates demand for digital lenders in their capacity of providing a new borrowing path.

There is an evident timing mismatch between the character of borrowers' needs and traditional appraisal processes. Dire economic circumstances typically renders funding needs immediate and acute when a low-income borrower seeks credit. Nonetheless, the traditional credit appraisal process requires several administrative documents, background checks and meetings which may take months from application to disbursed funds. This misalignment was widely confirmed by the borrowers' experiences, not considering formal credit a viable alternative for mitigating economic shocks. In addition, hardship concerning the logistics and time spent on reaching bank branches for the administrative process is typically exacerbated for rural residents. The digital nature of the new entrants substantially decreased transaction and opportunity costs for borrowers. A credit expert illuminates the point: "It [digital lending] is like bringing a bank

branch to your pocket." (Interview 19) The digital-first operating model circumvents traditional mismatch of processes and infrastructure, yielding another significant driver of demand.

These structural conditions create a strong demand for short-term liquidity, explaining the widespread adoption of digital credit.

3.2.2 Digital credit as emergency finance

Digital credit is shown to primarily serve as a consumption smoothing device. The structurally induced short-term liquidity constraints typically affect household's ability to cater for their essential consumption needs. Although digital credit is financing operating capital to a degree, small ticket sizes constrains the types of available productive uses of capital. Respondents therefore frequently channel funds from digital credit towards grocery shopping, the daily commute and rent payments. Nevertheless, among higher income-groups of the population, it is convenience rather than economic precarity which motivates the use of digital credit as consumption smoothing. "You've just found yourself at a till [payment interface], you need to pay for something and realize you don't have the money in your wallet." (Interview 2) Thus, interview evidence suggests that digital credit primarily functions as short-term liquidity support rather than productive investment capital.

We find that the most common type of consumption smoothing is 'emergency finance'. 'Emergency finance' refers to borrowing situations where the individual is in acute need of financing the resolution of an immediate concern. Frequently reported emergency finance situations include the need to pay for medical bills to enable the discharge of family members from a healthcare clinic, insufficient funds to cover a relative's funeral costs or inability to pay for children's school fees. A resident in the Kibera slum exemplifies: "I had an emergency [inability to pay university fee], so I asked my mom for money. She did not have any money so she told me that I can take a loan through an app called Tala." (Interview 17) The short-term liquidity support provided by digital credit is therefore regularly channeled towards impactful consumption smoothing activities.

3.2.3 Borrower heterogeneity and welfare outcomes

Digital credit usage is found to be welfare-enhancing for stable yet liquidity constrained individuals. Stability is here defined as being the recipient of regular and predictable income or being the proprietor of an asset whose cash-flow generation matches the short-term character of

digital credit. Stability is required as it is a quintessential part of having adequate conditions to repay the loan. Liquidity-constraint, the inability to access funds elsewhere, is required for the impact of digital credit to be additional as other sources of funding typically bear more favourable terms.

In general, the first category of stable individuals are formally employed individuals who can use their expected future income to effectively incorporate digital credit as a funding source in their financial planning. The second category of stable individuals involves entrepreneurs with viable business models. Two primary examples of this are Uber and Boda Boda (motorcycle) drivers, which are highly demanded modes of transport in Kenya (and Nairobi in particular). For them, the existence of digital lenders may enable business continuity by bridging liquidity constraints, such as financing refuelling or maintenance expenses. As this Uber driver phrased it: "It's very good for people like us who [drive for] Uber, because sometimes your car may be damaged, say the side mirror, and you don't have money. So you ask them [digital lenders] for 3000 KES to repair." (Interview 20) A third, and heterogenous, group who may put digital credit to productive use are the independently organized informal roadside vendors, which are referred to as 'Mama Mbogas' in Kenya. The prototypical example is a woman who travels to the city's fruit market in the early morning, financing her purchases with digital credit, then finds a suitable location to resell the fresh produce at a profit within the same day.

To generalize this finding, microentrepreneurs who can fund business activities whose cash flows arrive within the maturity of the loan while generating an economic profit (incorporating the cost of borrowing) may improve the livelihood of the individual. It is nevertheless noteworthy that these microentrepreneurs routinely mix their household and business expenditures, where economic shocks may divert funds intended for productive use cases towards consumption smoothing. Nevertheless, adequate repayment ability coupled to productive use cases allow welfare-enhancing effects of digital credit.

Digital credit is conversely more likely to amplify long-term economic vulnerability when used by unstable borrowers with volatile incomes. Volatile incomes are common among casual workers, the precarious self-employed and to some extent salaried individuals in low-income occupations. Casual workers supply their labour on a daily basis dependent on demand and fitting the requirements, with small to none economic outlook even over the short duration to maturity of a digital credit (Interview 3). Precarious self-employment involves 'entrepreneurs by necessity' who finance their livelihood through basic commerce which is highly sensitive

to demand fluctuations that may halt incomes over sustained periods of time (Focus group 1, Interview 15).

Even for salaried individuals in low-income occupations, such as gardeners, guards and nannies, job-security is typically low and it is not an exceptional phenomenon for the timing of salary payments to vary which makes the households vulnerable to the short loan maturities (Focus group 2). For these categories, individuals resort to the use of digital credit as 'survival borrowing', namely covering essential needs without certainty of repayment ability. The volatile incomes increases default probability and hence the cost of borrowing is typically accentuated by late repayment penalties, such as fees or additional interest. This typically triggers borrowing to repay outstanding debt, effectively creating a debt cycle. As a borrower recalls: "I have like 10 000 [KES] and I have to pay 13 000. What will I do to secure my [loan] limit? I'm going to take [borrow] 3 000 from another app to repay this and retain my limit." (Focus group 2)

While a spiralling debt cycle is the most grave outcome, it is not exceptional for individuals to fall into a structural credit dependency. Structural dependency is here defined as a household being unable to meet its day-to-day means without having an active digital credit. In practice, this typically occurs through immediate repayment of outstanding loans when receiving sufficient cash flow (i.e., salary, paid invoice) and then subsequently taking out another loan to pay for living costs such as monthly household expenses (e.g., rent, groceries). This was common practice among several participants in the focus group sessions (Focus group 1 and 2). An example of structural dependency: "You can have like four apps where you borrow from here to pay there, to pay there, to pay there until maybe the end of the month when you get a salary or you have some cash from your business. So in terms of financial planning it's not good at all, because you're not able to save because you're always in constant debt." (Interview 13) If structurally dependent on credit, being overindebted, the ability to use loans as consumption smoothing is heavily reduced as the borrowing costs are internalized with less financial leeway as a result. To conclude, volatile incomes are shown to serve as a predictor of experiencing adverse welfare effects related to digital credit overindebtedness.

Sizeable and lingering economic shocks is however likely to trigger debt distress regardless of borrower type. The effects of Covid-19 on Kenyan households' purchasing power and the subsequent cost of living crisis serves as an illustrative example of the devastating effects of lingering economic shocks on the usefulness of digital credit. During the economic downturn associated with Covid-19, respondents witnessed widespread layoffs resulting in a worsened

structural vulnerability and increased immediate demand for digital credit. Then, as the economy stalled during roughly two years, individuals defaulted on their loans. The subsequent increase in borrowing costs further aggravated households already weak economic circumstances. A gardener recounted that he was unable to repay his 5000 KES (~40 USD) loan during the two years following the Covid-19 pandemic, leading to a surge in interest amounting to 8000 KES (Focus group 2). In addition, he recalled being continually threatened over the telephone by debt collectors hired by the digital lender to recoup their losses (Focus group 2). Hence, the utility of digital credit as short-term liquidity funding and consumption smoothing device is lost when the economic shock is enduring.

Alongside traditional economic welfare effects, evidence indicates considerable emotional suffering coupled to overindebtedness and digital lenders' market misconduct. Individuals who endure structural debt dependency or simply experience the repercussions of defaulting on digital credit regularly experience psychological distress caused by the inability to settle their debts. A prevailing source of trouble regards 'debt shaming', which an overwhelming majority of interviewees reported being subject to. Debt shaming is the act of calling individuals in a borrower's phonebook without their consent, e.g., relatives, friends, employer, pastor, to inform about the outstanding debt as a means of asserting pressure for the indebted to repay. The experience of being subjected to debt shaming is often referred to as embarrassing, shameful, stressful, a privacy violation and induces substantial angst in the victim. Described in the following manner by a borrower: "Of course it was bad. It's terrible, terrible. It exposes you. You can imagine if you take a loan and the company starts calling your friend saying that he needs to pay your loan, threatening him if he don't. It's not something you would like to happen to anyone." (Interview 12)

In addition, the feeling of abusing the borrower's trust is apparent: "It's embarrassing since it was just me and my phone, then why do you have to involve another person, a third party?" (Focus group 1). Notably, the calling is perceived as endless, perturbing everyday life and is not necessarily restricted to waking hours. The experience of overindebtedness may create significant pain and a sense of hopelessness: "We don't even sleep sometimes. You have a loan from this one, a loan from that one and then your loved one gets sick. You can't go to your boss because there is a loan, you have already gone to the Chama, you already have a loan from the apps and then comes a sickness inside. It is very stressful." (Focus group 2)

The emotional repercussions from debt distress when evaluating the rise of digital credit in

Kenya is therefore rather important; omitting it from the analysis would yield a reductive and incomplete image of the actual impact on individuals' welfare.

3.2.4 Digital credit and financial literacy

Opaque loan terms is found to render it difficult to accurately gauge the total cost of borrowing. Borrowers reported varying degree of awareness on the loan terms of their digital credit product. This varying awareness is related to financial literacy, as the marketing pursued by digital lenders typically tends to emphasize the speedily and sizable disbursement while framing the costs as minimal, requiring the individual to evaluate the covenants of the loan themselves. It was an impossible practice for some in the period before regulatory oversight, as a borrower recounts being sent the terms and conditions only after having received the disbursed funds (Interview 24). Several interviewees were also surprised about the additional costs associated with late repayments, such as doubled interest rate.

In addition, the short-term character of the loans makes gauging the costs more difficult among less financially literate parts of the population. For instance, borrowers experienced a disconnect between the perceived affordability of a 10% monthly loan, which was considered decent, and feeling trapped by spiralling interest payments when having come to structurally rely on debt. As put by a disappointed borrower: "Like you see this interest part is where they steal the money from you. So in your brain you're like it's just one month, I can afford this loan of 11 500 KES. And when you tell them that you have a difficulty in repaying, then they tell you that you can still pay it after two months. They don't tell you that in two months you have to pay 13 000 KES, that the interest doubles." (Focus group 1) Borrowers' inability to gauge loan terms therefore hinders their ability to choose less costly digital credit alternatives, potentially exacerbating adverse welfare effects while maintaining demand for digital lenders with extortionate terms.

In theory, financial literacy could mitigate the uptake of digital credit by enabling borrowers to differentiate between loan terms to decrease the demand for lenders offering usurious terms. Financial literacy interventions are however unlikely to have a transformative effect on the uptake of digital credit as borrowers' urgent demand decreases its capacity to serve as an effective screening device. This is related to the fact that the perceived utility of accessing funds is typically higher than the cost, due to the urgency of the economic situation at hand, regardless of loan terms. For instance, financially literate university students reportedly fell into

overindebtedness as the demand for and ease of accessing funds trumped their adequate capacity to evaluate the terms of the offered product (Interview 1). A financial policy expert expressed it distinctly: “When somebody is taking out the (digital) loan, the urgency overrides financial literacy. By the time they are applying, they have exhausted all other pathways.” (Interview 2) Thus, the urgent borrowing situation reduces the price elasticity of demand, overriding hypothetical effects of improvements in financial literacy.

3.2.5 Risk transfer beyond borrower fundamentals

A substantial degree of risk is implied from the fundamental information asymmetry issue which permeates the lending market, i.e., inability to distinguish good borrowers from bad, exacerbated by non-existent or flawed credit histories. While the leveraging of alternative data nevertheless enables underwriting for digital lenders, the borrowers’ risk profiles remain significantly higher than for the average bank customer. Simultaneously, expensive commercial interest rates and aggressive growth expectations exerted by venture capitalists are driving continuous loan book expansion among lenders (Interview 9). If not constantly extending new loans, they may face liquidity concerns for their debt service and discontent from investors. The terms and conditions of digital credit products are consequently designed in a way to mitigate and minimize lending risks while simultaneously supporting the lenders’ ambitious growth expectations.

The resulting traits of digital lending point towards risk transfer in several ways. First, the default risk is pre-priced in the high interest rates. This is illustrated by the interest rates typically being almost twice for first-time borrowers compared to repeat customers, 15% vis-à-vis 7–8% (Interview 11). Second, the low initial loan limit and slow progression implicitly incentivises rapid early repeat borrowing to advance the loan limit level until it can cater for real borrowers’ needs. As such, the digital lender minimizes the value at risk by only losing a marginal amount if the borrower fails early and having made a net-profit on the borrower through previous transactions with its high loan margins if the default arrives at a later stage. Then, the usage of late-repayment penalties, typically a doubled interest rate, serves as another risk-transferring mechanism which substantially increases the borrowing costs. Last, threatening with a negative listing at the credit referencing bureaus serves as a disciplining and externalized measure which asserts further pressure and risk onto the borrower. Evidence therefore points toward a significant risk transfer from the lender to the borrower, the transfer improving the commercial conditions for lenders by effectively worsening loan terms for the borrowers and thus simultaneously decreasing borrowers’ repayment capacity (or probability).

This risk transfer is pursued while disregarding, to a degree and depending on lender, the borrowers' economic fundamentals. The current lending mandate in Kenya, of which digital credit is no exception, is rules-based lending (Interview 19). The automated algorithms for digital credit appraisal is a machine that is checking boxes to minimize value at risk rather than adjusting prices based on risk level. The standard, almost commoditized, offering towards the mass-market incorporates the risk of all potential borrowers. It therefore refrains diligent repayers, 'good borrowers', from accessing affordable credit as they must carry the costs from non-performing, 'bad borrowers' (Interview 9). In addition, the automated loan limit progression typically disregards borrower fundamentals such as monthly incomes, as several interviewees have artificially boosted their loan limits through loan stacking and debt cycling until the monthly loans exceeded their incomes (Focus group 2). Exemplified by the following borrower: "Then you know very well that you have borrowed more than your income and the money is not enough, so you have to go to another. Like you borrow from like five apps here to pay there and that." (Focus group 1) The risk transfer is effectively transmitting accountability to the borrower, who do not typically have adequate baseline conditions to effectively handle the risk, increasing the risk of overindebtedness and debt distress.

3.2.6 Regulatory implementation challenges

The liberal and innovation-oriented regulatory ideology in Kenya allowed for the proliferation of digital credit without early intervention. Notably, the ideology shaping Kenya's regulatory environment is more liberal and less interventionist compared to other African counterparts. Choosing not to pursue full nationalization of the banking sector at independence serves as an illustrative example (Interview 1). Specifically, the ideology favours 'laissez-faire' market dynamics and private sector competition while prioritizing a strong financial sector. A digital credit researcher was explicit: "Kenya is generally a very permissive regulatory market. The ideology is very pro private sector, pro finance, pro market." (Interview 1) Furthermore, this ideology supports the idea of 'free private lending' which refers to unscrutinized disbursement of funds with private contracts on loan repayment terms where the private lender bears the risk and is responsible for debt collection. As such, it is regarded as a private affair and should not be subject to government interference. This notion was concisely summarized by a digital financial services bank director: "If you have the money to lend, that's your problem. Go ahead and lend it. You're the one taking the risk." (Interview 18) This is important as the permissive regulatory approach in Kenya created leeway for digital lenders to expand.

Alongside a permissive governing ideology, digital credit fell between existing regulatory mandates, delaying regulatory oversight. The prevailing regulatory architecture in Kenya is marked by distinct sectorial mandates based on each regulatory authority having a separate primary legislation which governs its activities. A financial policy expert stressed the importance of the primary legislation as it defines the objectives and function of the authority, which tend to be rather narrow to avoid overlap across agencies (Interview 2). For instance, the Central Bank of Kenya regulates commercial and microfinance banks yet does not, per se, have a mandate to oversee the activity of credit provision in broader terms. This role is shared with other authorities, such as the SACCO Societies Regulatory Authority (SASRA). This sectorial regulatory approach created a vacuum for digital lenders which did not fall under either of the different regulatory mandates.

To give an illustration, the Central Bank of Kenya's original and primary mandate revolved around overseeing the bank sector where the key activity concerns public deposit-taking. In this assignment, the authority's priority is to safeguard financial stability and protect consumers' savings. A persuasive argument provided by a financial policy expert on why the Central Bank of Kenya did not initially wish to oversee digital lenders was the fact that they did not pursue deposit-taking and therefore fell outside their mandate (Interview 2). The sectorial division of regulatory mandates in the financial sector delayed regulators' initiative to regulate the sector, as none considered them their primary concern.

The regulation is also likely to have had less profound effects due to the complicating factors surrounding oversight of the digital credit industry. First, the practically nonexistent entry and exit barriers allowed for a proliferation of actors. A financial policy expert summarized the entry barriers bluntly: "If you had a balance sheet, you could publish an app in the App Store and start lending off your books." (Interview 2) Second, operating in regulatory shadows allowed actors to be anonymous, making it hard for regulators to gauge the structure of the digital lender. Common traits of digital lenders therefore included operations without physical addresses, no contact information on management nor ownership, and opaque funding sources. Third, the proliferation of digital lenders may have taken the Central Bank of Kenya by surprise, which was used to govern fewer yet larger institutions. As phrased by this digital financial services expert: "What the regulator wasn't prepared for was that by the time we were getting to 2021, we had grown from a few tens or twenty entities to now several hundred." (Interview 8) The number of digital lenders operating with, without and awaiting licenses thus blurred

the lines and impeded regulatory oversight. Thus, low entry and exit barriers, the stealth-like nature and proliferation of digital lenders obstructed effective regulation of the industry.

Enforcement constraints appear to have also played a role in curbing regulatory implementation efforts. While the Central Bank of Kenya (Digital Credit Provider) Regulations 2022 contains comprehensive and prescriptive juridical language, qualitative evidence points towards several enforcement challenges. First and foremost, there are several accounts of the Central Bank of Kenya being understaffed with regard to their obligations of providing oversight of digital lenders. Interviewees point towards a substantial burden already carried by the Bank Supervision Department, which is responsible for not only digital lenders yet also forex bureaus, commercial banks, money remittance providers, microfinance institutions and credit referencing bureaus. A financial policy expert is still calling for a dedicated market conduct section, to better grapple with the existence of digital lenders: "I think at a minimum there needs to be a separate department that just looks after market conduct and personal protection." (Interview 2)

In addition, the licensing process is considered onerous by digital lenders, especially the fit and proper requirements and the manual nature of the process. This proved difficult for the Central Bank itself, as recalled by a digital lender: "When they launched the regulations, they got overwhelmed. So, this shocked their system considerably and they were therefore unable to meet their promised licensing deadlines. So over the next two years, it was a grueling time where many of us were unable to get licenses." (Interview 8) Thus, the spare capacity was low and the backlog immense, leading to a situation where there are hundreds of actors in the market which may continue their operations without being licensed. As of writing, the licensing backlog remains, indicating lasting constraints with regard to providing regulatory oversight of the industry. The enforcement constraints align with our quantitative findings showing a limited measurable impact of regulation, as practical implementation is found to be substantially delayed.

Self-regulatory efforts have played an active part in influencing the regulatory architecture surrounding digital credit. While the misconduct of digital lenders is typically more acute among smaller actors, the public resent nevertheless yielded a holistic negative perception of digital lenders. This posed a critical risk to the industry's reputation according to representatives of more established digital lenders. As phrased by an industry leader: "We had created such a bad reputation over the years that the governor of the Central Bank had taken a position where he wanted nothing to do with digital lending, it had become a pariah in Kenyan society." (Interview

8) This prompted the more professional actors to proactively engage in self-regulation and establish themselves as a serious actor by drafting the Digital Lenders Association of Kenya's Code of Conduct.

A major motivation behind the initiative was a reputational incentive, namely to acquire the minimum social capital required from the regulator to allow for inclusion in stakeholder dialogue (Interview 8). This was proven to be a fruitful effort, with extensive stakeholder dialogue in the drafting of legislation surrounding digital credit ahead of the introduction of the regulations. Further, an industry leader mentioned that it was the digital lenders' idea to introduce a two-tiered system which is proposed in the current draft regulations, as a way of easing the regulatory burden at the Central Bank. As such, amidst capacity constraints in the public administration, industry players and experts believe that self-regulatory efforts will continue to complement the official regulation in sharing the responsibility of making regulation more effective with the joint goal of decreasing consumer harm caused by digital credit (Interview 2).

3.2.7 Regulatory outcomes

While the regulatory effort is pursued in a challenging environment, both industry experts and borrowers observe differences in market conduct after the introduction of the regulation. The majority of these effects relates to the fact that the regulation formalized the sector by introducing a license, effectively differentiating legitimate actors in the industry.

Compliance with the Kenyan Data Protection Act emerged as a key difference after the regulation. Specifically, a licensing requirement forced digital lenders to register as data processors and controllers under the Data Protection Act (Interview 7). While the majority of complaints regarding data protection violations to the Office of the Data Protection Commissioner in Kenya still concerns digital lenders, there has been a substantial decrease in reports and a significant improvement in data handling practices among the digital lenders (Interview 4). Consequently, borrowers note that debt shaming is less prevalent among formal digital lenders whereas it continues to be an issue among smaller operators without licenses. An Uber driver described his experience in the following way: "Nowadays they call less and they are more courteous." (Interview 26) Thus, there exists a perception that market misconduct related to debt shaming has decreased somewhat, although the extent of the phenomenon is hard to gauge.

Visible, stable and accessible loan terms among licensees is another benefit stemming from the regulation. Industry experts note that a key proponent of the legislation involves that digital

lenders must obtain approval on their proposed loan terms from the Central Bank of Kenya before starting commercial operations, and they must seek renewed approval for any changes to the terms. This decreases the room for extortionate pricing and overnight changes of loan terms (Interview 19). In addition, the loan terms must be visibly displayed on their website and in the mobile application before any signing of contract. This is positive as, in the nascent days of digital credit, individuals report having seen the loan terms merely after signing the contract of the loan (Interview 24). Nonetheless, borrowers still seek loans from unlicensed actors who do not follow the Central Bank of Kenya's pricing model and we did not observe a general perception of improved pricing among interviewees.

Improved data reporting practices and a more transparent credit information sharing ecosystem were found to be other key results of the regulation. In particular, the regulation introduced a mandate requiring positive and negative credit reporting among digital lenders, which have yielded a significant change from low initial levels of voluntary reporting. Today, circa 80% of digital lenders actively report credit information to at least one credit referencing bureau (Interview 19). Furthermore, there is substantial ongoing cooperation among the Central Bank of Kenya, the Credit Information Sharing Association of Kenya, the Credit Referencing Bureaus and the digital lenders to standardize the available credit information, with the shared intent of decreasing the degree of credit information asymmetry in Kenya (Interview 5). A digital lending industry leader phrased it in the following way: "Let us have a similar data structure so that the conversation becomes about people's credit scores." (Interview 8) The regulation therefore incentivised improved credit reporting and supported a larger shift in the ecosystem which carries the intent to shift from rules-based to risk-based lending.

3.2.8 The perception and appeal of digital lenders

Digital lenders emerged as a socially legitimate actor in Kenya with a general approval on their role of extending credit to marginalized groups. While borrowers do not necessary trust the digital lenders, there exists a general positive perception of them. In particular, the digital lenders are perceived as supportive, helpful and as actors who are having a positive impact on local communities. As this borrower asserted: "Soft loan providers? They are good, because they are helping. We need them in Kibera [Kenya's largest slum]." Moreover, digital lenders are typically preferred to shylocks and microfinance banks as they are considered less costly, less likely to seize assets and more anonymous (Interviews 12, 15, 19 and Focus group 1). Nevertheless, other stakeholders oftentimes consider the loan terms exploitative, citing extortionate interest

rates and insufficient underwriting. The borrowers themselves also perceive digital lenders as expensive and therefore relate to them as 'a lender of last resort'. Another obstacle includes the short repayment periods, with focus group members suggesting an extension to two months for facilitated debt service. Still, digital lenders are holistically perceived to serve the needs of lower-income parts of the population.

While the role itself is appreciated, the principal appeal and distinguishing feature of digital lenders is the substantially reduced friction in the user experience of acquiring credit. Digital lenders did not solely lower the barriers to credit by replacing the need of travelling to a bank branch, the automated process leverages existing data which minimises the time and effort required by the borrower. Specifically, the application process merely involves registering your identification number, perhaps a photograph to validate, and then a standardized submission of M-PESA statements (while submitting legal access to other types of data). Thus, there is no substantial preparation, interaction nor documentation needed, as everything is simplified through the digital interface in the mobile application. Then, the automated process allows for the remote and instant disbursement of funds, which is one of the most appreciated traits among borrowers. The excitement was palpable by the following borrower: "If you have been clearing [approved], it takes like two minutes and the money is on your phone. Sometimes even a minute or mere seconds!" (Focus group 2) The simple, quick and hassle-free process of accessing digital credit hence reduces the threshold for credit uptake, facilitating the use of digital credit as emergency finance.

Taken together, the qualitative findings paint a picture of a digital credit market that fills a genuine and pressing need in the Kenyan financial landscape, yet one in which structural vulnerability, misaligned loan terms and persistent regulatory implementation challenges combine to produce welfare outcomes that are deeply heterogeneous across borrower types. The 2022 regulations have begun to shift market conduct in meaningful if incomplete ways. The institutional and enforcement constraints documented above nevertheless suggest that the gap between regulatory intent and borrower experience remains substantial. We seek to interpret this tension in the discussion below, accounting for both the quantitative and qualitative evidence.

4 Discussion

The discussion that follows integrates the findings from both the household survey analysis and the qualitative fieldwork around three themes: the structural role of digital credit in the Kenyan financial landscape, the impact of the 2022 regulations as illuminated by the combination of quantitative and qualitative evidence, and the policy implications that emerge from this analysis. Limitations of the study are addressed at the end of the section.

4.1 Digital credit as a structural phenomenon

The qualitative findings establish that digital credit in Kenya operates not as a standalone financial product but as a structural response to the absence of adequate social protection and the persistence of income volatility among low-income households. This framing is consequential for how its welfare effects should be interpreted. Where previous studies have evaluated digital credit primarily as a consumption-smoothing or investment tool, asking whether it raises incomes or improves household resilience, our evidence suggests that for the majority of borrowers, digital credit is first and foremost a substitute for social security, used to finance emergency expenditures in the absence of any viable alternative. This usage pattern is consistent with Suri et al. (2021)'s finding that M-Shwari loans are predominantly directed toward health emergencies, but it goes further in identifying the structural conditions, i.e., underdeveloped social insurance, high income volatility and persistent exclusion from formal credit, that make such usage widespread among lower-income borrowers rather than a contingent individual choice.

This structural usage pattern has direct implications for the welfare potential of digital credit. Emergency expenditures directed at consumption needs do not constitute investment in productive assets and therefore cannot trigger the asset accumulation dynamic that Balboni et al. (2022) identify as necessary to cross a poverty trap threshold. Rather than serving as a stepping stone out of poverty, digital credit as emergency finance is more likely to sustain subsistence-level consumption without altering the underlying asset position of the borrower. This interpretation is reinforced by the loan characteristics of digital credit itself: low average ticket sizes and short repayment maturities structurally constrain the range of productive uses to which the credit can be put, a mechanism previously identified by Brailovskaya et al. (2024). The resulting picture is consistent with the broader microcredit literature, where Banerjee et al. (2015) and Meager (2019) similarly fail to identify transformative welfare effects. Thus, the digital delivery mechanism lowers transaction costs substantially, but does not resolve the

fundamental tension between the character of the credit and the scale of investment required for lasting welfare improvement.

Our qualitative findings further stress that the heterogeneity of welfare outcomes is systematic rather than random, as it is linked to income stability in a specific and predictable way. Positive welfare effects appear to be concentrated among borrowers who combine two traits simultaneously: the ability to direct digital credit toward productive use, and adequate repayment capacity grounded in regular and predictable income. Formally employed individuals and microentrepreneurs with viable, short-cycle business models, such as Uber drivers, broadly meet both conditions. However, the majority of Kenyan households do not, given the predominance of casual and informal employment characterised by highly volatile incomes. This finding complicates the conclusion by Beck et al. (2007a) that reduced credit market frictions disproportionately benefit the poor: where the terms of the credit product, its cost, maturity structure and appraisal logic, are calibrated to the risk profile of thin-file borrowers rather than to their repayment capacity. Hence, the distributional benefits of financial access may accrue primarily to those with sufficient income stability to manage the product safely. Identifying income stability as the systematic predictor of welfare outcomes represents one of the central contributions of this study to the digital credit literature, as this mechanism has not been explicitly documented in prior research despite its policy relevance.

Beyond the economic dimensions of welfare, the qualitative evidence reveals a significant and underappreciated harm associated with digital credit overindebtedness: the emotional and social costs of debt shaming. Borrowers across income levels and contexts described being subjected to unsolicited calls to relatives, employers and community members disclosing their outstanding debts. This practice is experienced as deeply humiliating, anxiety-inducing and disruptive to daily life, including sleep and working routines. These dimensions of borrower welfare are inaccessible to purely quantitative analysis and are consequently absent from existing empirical studies on digital credit outcomes, including those that otherwise provide rigorous welfare assessments (Suri et al., 2021; Brailovskaya et al., 2024). Their omission from the literature produces a systematically incomplete picture of the costs associated with digital credit default, and by extension an incomplete basis for consumer protection policy. That the 2022 regulations appear to have reduced, though not eliminated, debt shaming among licensed lenders is therefore not a minor incidental finding, but a meaningful welfare improvement that aggregate survey data would be unlikely to detect.

4.2 Regulatory impact

The quantitative analysis finds that the 2022 Digital Credit Provider Regulations had limited measurable effects on borrower outcomes in the short term. Across the four outcome variables examined, the most significant signal is a modest reduction in debt distress among counties with high pre-regulation exposure to digital lending, though the validity of the parallel trends assumption for this outcome is not fully supported by the pre-trend evidence. Effects on digital app loan default rates, financial resilience and the ability to meet basic needs are small and statistically insignificant. Taken at face value, these estimates suggest that the regulation did not materially alter the financial health of digital credit borrowers in the two years following its introduction. One potential reason for the small estimates in the remaining outcome variables could be the natural pace at which the variables change, especially when looking at financial resilience. While debt distress practices, such as selling assets or undertaking new loans to repay loans, are behaviors that are more easily changed, improving financial resilience requires changes in saving behaviour and the accumulation of savings buffers, both of which take considerable time to materialise. This could explain why we do not observe significant short-term effects on financial resilience in our analysis.

However, taken alone they are difficult to interpret: a null result in a difference-in-differences design can reflect the absence of a true effect, the presence of an effect that the data are insufficiently powered to detect, a violation of the identifying assumptions, or, crucially, an effect that is real but that operates through channels the outcome variables do not capture. The qualitative evidence allows these possibilities to be distinguished with considerably greater precision than the quantitative analysis alone permits.

The qualitative findings converge on a coherent account of why transformative regulatory impact was unlikely in the short term. Four institutional factors emerge as particularly consequential. First, the pre-existing regulatory ideology in Kenya is explicitly market-oriented and resistant to strong intervention, creating a political environment in which the regulation was designed with a relatively light licensing touch rather than as a prescriptive conduct framework. Second, the structural legacy of sectorial regulatory mandates meant that digital lenders initially fell outside the jurisdiction of any single authority, delaying oversight by several years and allowing the market to scale well beyond the Central Bank's supervisory capacity before regulation was introduced. Third, the proliferation of actors, with hundreds of digital lenders operating simultaneously, many without physical addresses or transparent ownership structures, created

an oversight challenge of a fundamentally different character from the Central Bank's traditional remit of supervising a small number of large, visible institutions. Fourth, the licensing process itself generated a substantial backlog, leaving a large share of the market in a regulatory grey zone for an extended period after the 2022 Regulations came into force. Each of these factors individually would be sufficient to constrain the immediate impact of a regulatory intervention; their combination helps explain why the quantitative estimates are as modest as they are.

Where the two methodological parts speak most directly to one another is in the interpretation of the debt distress finding. The quantitative analysis identifies a statistically significant reduction in debt distress among high-exposure counties following the regulation, but the pre-trend evidence introduces sufficient uncertainty that a straightforward causal interpretation is difficult to sustain on quantitative grounds alone. The qualitative evidence provides an independent and complementary line of reasoning: borrowers and industry experts across multiple interviews and both focus groups consistently report a reduction in debt shaming among licensed digital lenders following the regulation, attributing this specifically to the requirement that lenders register as data processors and controllers under the Data Protection Act, which constrained the unsolicited contact of third parties. Since debt shaming creates acute social and psychological pressure to repay, it may plausibly drive the distress behaviours captured in the index, i.e., asset sales and emergency borrowing to settle outstanding obligations. A reduction in such practices among licensed lenders could therefore translate into fewer households resorting to these measures. The qualitative mechanism therefore provides a behavioural pathway that is consistent with the quantitative signal.

A further point of integration concerns what the regulation did not achieve. The quantitative findings show no significant effect on default rates, financial resilience or the ability to meet basic needs. The qualitative evidence suggests a straightforward explanation: the persistent demand for short-term liquidity among financially vulnerable households, driven by structural vulnerability rather than preferences, means that borrowers continue to seek credit from unlicensed lenders when licensed alternatives are unavailable or insufficiently accessible. The regulation formalised the sector and improved conduct among licensed actors, but it did not alter the underlying conditions that generate demand for digital credit in the first place, nor did it achieve the market coverage necessary to discipline the unlicensed segment. The limited quantitative impact on financial outcomes beyond debt distress is by itself a meaningful finding: it reflects the boundary of a licensing-based regulatory intervention in the absence of complementary structural reforms.

4.3 Policy implications

The findings of this study carry implications for the design and implementation of digital credit regulation in Kenya and in other developing country contexts where comparable regulatory questions are being actively debated. Three implications merit particular attention.

The first and most immediate concerns enforcement capacity. The qualitative evidence documents that the Central Bank of Kenya's Bank Supervision Department was substantially under-resourced relative to the scale and character of the market it was tasked with overseeing. The department's existing mandate already covered commercial banks, microfinance institutions, forex bureaus, money remittance providers and credit referencing bureaus; the addition of hundreds of digital lenders, many of them small, opaque and operating without physical infrastructure, represented a qualitatively different supervisory challenge for which the department's existing staffing and systems were not designed. The licensing backlog that resulted left a large proportion of the market effectively unregulated for an extended period, undermining the reach of an otherwise comprehensive legislative framework. This points toward a general principle of considerable relevance to regulators beyond Kenya: the binding constraint on regulatory effectiveness in rapidly scaling digital financial markets is frequently not the design of the legislation but the institutional capacity to implement it. A two-tiered licensing system, as proposed in Kenya's current draft regulations and credited by industry participants to the digital lenders' own advocacy, represents one promising approach to managing this constraint; by differentiating regulatory requirements according to the scale and risk profile of lenders, it may allow supervisory resources to be concentrated where consumer harm is most acute. Whether such a system would be effective in practice remains an important question for future research.

The second implication concerns the relationship between consumer protection regulation and structural economic vulnerability. The qualitative evidence suggest that demand for digital credit in Kenya is rooted in structural conditions, the absence of adequate social protection, the prevalence of informal and volatile employment, and the persistent exclusion of low-income households from formal credit, rather than in informed preferences for a specific financial product. This has a direct implication for the scope of what consumer protection regulation can achieve: improving lender conduct, increasing transparency of loan terms and restricting predatory collection practices are meaningful welfare improvements, but they do not address the conditions that drive borrowers toward expensive, short-term credit in the first place. For

the segment of the population most at risk of adverse welfare effects, those with volatile incomes who use digital credit as survival borrowing, the root cause of harm is not inadequate regulation of lenders but inadequate social insurance. This suggests that digital credit regulation, however well-designed, should be understood as a complement to rather than a substitute for broader social protection reform, a policy priority that lies outside the Central Bank's mandate but within the remit of the wider development agenda in Kenya and comparable economies.

The third implication relates to the potential of self-regulatory mechanisms as a complement to formal oversight. The qualitative evidence reveals that the larger and more established digital lenders developed a Code of Conduct through the Digital Lenders Association of Kenya prior to the introduction of the 2022 Regulations, motivated substantially by reputational concerns and the strategic goal of achieving legitimacy in the eyes of the regulator. This self-regulatory effort preceded and arguably shaped the formal regulatory framework, with industry participants credited with proposing the two-tiered licensing model currently under development. This dynamic, in which commercial incentives among established actors align with regulatory goals around disciplining predatory behaviour among smaller operators, represents an underexplored mechanism for extending the effective reach of regulation beyond the formal perimeter of licensed actors. Where supervisory capacity is constrained, regulators may find it productive to formalise and incentivise such self-regulatory arrangements rather than relying exclusively on direct enforcement. The Kenyan experience suggests that this approach can be a practical complement to formal oversight, though its limitations, including the risk that self-regulation is designed primarily to serve incumbent interests rather than borrowers, should be acknowledged and monitored.

4.4 Limitations

Several limitations bound the causal and generalizable claims of this study and should be borne in mind when interpreting the findings.

In the quantitative part, the most significant constraint concerns the repeated cross-sectional structure of the FinAccess data and the relatively short pre-regulation window available for assessing the parallel trends assumption. All outcome variables suffers from a short pre-regulation window which reduces the ability to trace causal estimates. However this concern is especially prevalent for digital app loan default, where the pre-trend spans only two pre-period data points due to the variable's absence from the 2016 survey wave, which limits the ability to assess

whether treated and control counties were on comparable trajectories prior to the intervention. The parallel trend condition is also a cause of concern when looking at our debt distress estimates. While the evidence for the pre-trend points towards comparability between treatment and control counties in our event study specification, the placebo test points in the opposite directions showcasing significant estimates prior to the intervention, potentially driving the effect we see in our main result. As mentioned earlier, this may be attributable to prior events having heterogeneous effects e.g the Covid pandemic which cannot be fully absorbed by the year fixed effects.

Another data limitation concerns the risk of compositional bias, which the robustness checks including the alternative IPW specifications and the regression covering 2021–2024 only highlight. The estimates from IPW specifications are broadly consistent with the main results, which provides some reassurance that the findings are not driven by compositional bias or model dependence. However, the findings from the 2021-2024 regression illuminates a potential risk for compositional bias driving our results as the differences in estimates are more pronounced here. These findings do not invalidate the quantitative results, but that they should be interpreted with these limitations in mind.

A third data limitation is that all outcome variables are self-reported, which introduces the possibility of social desirability bias and recall error, particularly for sensitive variables such as default and debt distress. These concerns are inherent to survey-based research in this context and are not unique to this study, but they should inform the confidence with which specific point estimates are interpreted.

The modest variation in digital app loan uptake between treated and control counties also serves as a limitation in our treatment design. The uptake varies from 0 to approximately 10% with most counties clustered at 0 to 5% . This narrow range of uptake usage across counties could have an effect on our estimates, as counties close to cutoff share little difference between them, potentially biasing our results towards zero.

A final limitation concerning the household survey analysis is the potential mechanical bias affecting the outcome variable digital app loan defaults. As our treatment design builds on digital app loan prevalence, the outcome effect on digital app loan defaults could be partly mechanical, since more outstanding loans yields more opportunity for potentially defaulting on such loans. Due to this, the estimates on digital app loan defaults could be biased upward, limiting our ability to draw causal inference here.

In the qualitative part, two limitations are particularly important. The first is the geographic concentration of data collection in Nairobi. While Nairobi is the largest and most economically significant city in Kenya and the primary market for digital lending, the qualitative findings may not fully reflect the experience of borrowers in rural counties, where income patterns, social structures and access to alternatives differ materially. In particular, the heterogeneous welfare effects identified in the qualitative analysis, structured around the distinction between stable and volatile-income borrowers, may manifest differently in agricultural or pastoralist contexts where income seasonality matters more than for the urban informal sector. Pursuing additional interviews with rural communities would have further nuanced this dimension of the analysis. The second limitation is the absence of the Central Bank of Kenya's perspective. Despite repeated outreach efforts, including referrals through other interviewed stakeholders, no representatives of the Central Bank participated in the study. This is a meaningful gap given that the regulatory implementation process is a central object of inquiry: the account of supervisory capacity constraints and licensing challenges presented in the qualitative results rests exclusively on the perspectives of industry participants, researchers and other experts, whose characterisation of the regulator's limitations may not fully capture the institutional reasoning behind the choices made.

5 Conclusion

This paper set out to examine three questions: what role digital credit plays in the financial lives of Kenyan borrowers, how access to digital credit affects borrower welfare, and to what extent the 2022 Digital Credit Provider Regulations have influenced borrower outcomes and market conduct. Addressing these questions required a methodological approach that could operate simultaneously at the level of aggregate population outcomes and at the level of institutional mechanisms and lived experience. The mixed-methods design adopted here, i.e., combining household survey analysis of four waves of FinAccess data with qualitative fieldwork comprising 28 interviews and two focus group sessions in Nairobi, proved essential to that task.

The central empirical finding is that digital credit in Kenya functions primarily as a structural coping mechanism rather than a vehicle for productive investment. Demand is generated not by preferences for a particular financial product but by the intersection of three structural conditions: underdeveloped social protection, high income volatility among informal and casual workers, and persistent exclusion from formal credit markets. In this context, digital credit fills a genuine and pressing need, e.g., providing emergency finance and consumption smoothing that borrowers value highly and would otherwise be unable to access, but its welfare effects are deeply heterogeneous and systematically linked to borrower type. Liquidity-constrained borrowers with stable, predictable incomes can use digital credit productively and repay reliably within the short maturities on offer. Borrowers with volatile incomes, who constitute the majority of the Kenyan population, face a structural mismatch between their cash flow patterns and the character of the product, making debt cycling, overindebtedness and structural credit dependency common outcomes. This finding extends and formalises an intuition that is present but underdeveloped in the existing digital credit literature: heterogeneous welfare effects are not random but predictable, and income stability is a defining factor.

The quantitative analysis of the 2022 regulations finds limited measurable effects on borrower outcomes in the short term. A modest and statistically significant reduction in debt distress is observed among high-exposure counties following the introduction of the licensing framework, but effects on default rates, financial resilience and the ability to meet basic needs are small and insignificant. These results should not be read as evidence that the regulation was inconsequential. The qualitative evidence establishes that the regulation achieved meaningful market formalisation, reducing debt shaming among licensed actors, improving transparency of loan terms and catalysing a significant shift toward standardised credit reporting. Nevertheless,

enforcement constraints, including a substantial licensing backlog and chronic understaffing of the supervisory function, prevented the regulation from achieving comprehensive market coverage. The persistence of a large unlicensed segment, sustained by borrowers' urgent and inelastic demand for short-term liquidity, meant that the underlying market dynamics remained largely intact.

Beyond their immediate empirical content, these findings carry implications for the broader agenda of digital financial inclusion in developing countries. The Kenyan case illustrates that consumer protection regulation, however well-designed, operates within a structural constraint: when demand for digital credit is rooted in the absence of social insurance rather than in informed preferences, regulation can reduce the harms associated with predatory lending but cannot address the vulnerability that generates demand for expensive, short-term credit in the first place. This points toward the need for complementary policy interventions, in social protection, in loan product design, and in the institutional capacity of regulatory bodies, that fall across multiple ministerial mandates and development agendas. Kenya's evolving two-tiered licensing system represents a promising institutional innovation worthy of further study and, potentially, adaptation in other developing country contexts facing comparable regulatory challenges.

Several specific research questions emerge from this study that future work should prioritise. First, the effectiveness of the proposed two-tiered licensing system deserves empirical evaluation once implemented: whether differentiating regulatory requirements by lender scale and risk profile succeeds in concentrating supervisory resources where consumer harm is most acute, and whether it reduces the size of the unlicensed market, are questions this study raises but cannot answer. Second, the finding that volatile-income borrowers are structurally ill-suited to the current digital credit product raises the question of whether extending loan maturities, as suggested by focus group participants, would meaningfully reduce debt cycling and overindebtedness without eliminating the liquidity benefits which render digital credit valuable to this population. Third, the qualitative evidence on debt shaming as a significant welfare harm that is invisible to survey-based outcome measures points toward the need for more comprehensive welfare measurement frameworks in digital credit research, incorporating psychological and social dimensions alongside standard financial health indicators. Addressing these questions through further mixed-methods and experimental research would substantially advance both the empirical literature on digital credit and the evidence base available to policymakers in Kenya and beyond.

References

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research*, 46(3), 399–424.

Balboni, C. A., Bandiera, O., Burgess, R., Ghatak, M., & Heil, A. (2022). Why do people stay poor? *The Quarterly Journal of Economics*, 137(2), 785–844.

Banerjee, A. V., Duflo, E., Glennerster, R., & Kinnan, C. (2015). The miracle of microfinance? Evidence from a randomized evaluation. *American Economic Journal: Applied Economics*, 7(1), 22–53.

Banerjee, A. V., & Newman, A. (1993). Occupational choice and the process of development. *Journal of Political Economy*, 101(2), 274–298.

Bannert, M., Müller, A., & Seitz, S. (2023). The impact of foreign industrial policy on the Swiss economy: Evidence from the EU's Juncker Plan. *SECO Economic Analysis Report*.

Bari, F., Malik, K., Meki, M., & Quinn, S. (2024). Asset-based microfinance for microenterprises: Evidence from Pakistan. *American Economic Review*.

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2007). Finance, inequality and the poor. *Journal of Economic Growth*, 12(1), 27–49.

Beck, T., Demirgüç-Kunt, A., & Martínez Pería, M. S. (2007). Reaching out: Access to and use of banking services across countries. *Journal of Financial Economics*, 85(1), 234–266.

Brailovskaya, V., Dupas, P., & Robinson, J. (2024). Is digital credit filling a hole or digging a hole? Evidence from Malawi. *The Economic Journal*, 134(658), 457–484.

Burgess, R., & Pande, R. (2005). Do rural banks matter? Evidence from the Indian social banking experiment. *The American Economic Review*, 95(3), 780–795.

Burlando, A., Kuhn, M. A., & Prina, S. (2023, February 17). Too fast, too furious? Digital credit delivery speed and repayment rates. IZA Discussion Paper No. 16451.

Caliendo, M., & Kopeinig, S. (2005). Some practical guidance for the implementation of propensity score matching. Discussion Paper No. 1588. Institute for the Study of Labor.

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

Cartwright, E., & Igudia, E. (2024). The case for mixed methods research: Embracing qualitative research to understand the (informal) economy. *Review of Development Economics*, 28(4), 1947–1970.

Central Bank of Kenya (2006). *Banking Act*. Nairobi: Central Bank of Kenya.

Central Bank of Kenya (2022). *Central Bank of Kenya (Digital Credit Provider) Regulations 2022*. Nairobi: Central Bank of Kenya.

Chen, G., & Mazer, R. (2016). Instant, automated, remote: The key attributes of digital credit. CGAP Blog.

Curtis, E. M., Garrett, D. G., & Ohrn, E. C. (2022). Capital investment and labor demand. NBER Working Paper No. 29485.

Dupas, P., & Robinson, J. (2013). Why don't the poor save more? Evidence from health savings experiments. *American Economic Review*, 103(4), 1138–1171.

FinAccess. (2024). *2024 FinAccess Household Survey: Access, usage, quality, impact*. Central Bank of Kenya.

FinAccess. (2021). *2021 FinAccess Household Survey Report*. Central Bank of Kenya.

FinAccess. (2016). *2016 FinAccess Household Survey Report*. Central Bank of Kenya.

FinAccess. (2019). *2019 FinAccess Household Survey Report*. Central Bank of Kenya.

Galor, O., & Zeira, J. (1993). Income distribution and macroeconomics. *The Review of Economic Studies*, 60(1), 35–52.

Gwer, F., Odero, J., & Totolo, E. (2019). *Digital credit audit report: Evaluating the conduct and practice of digital lending in Kenya*. FSD Kenya.

Hwang, B., & Tellez, C. (2016). *The proliferation of digital credit deployments*. CGAP.

Jack, W., & Suri, T. (2014). Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. *American Economic Review*, 104(1), 183–223.

Johnen, C., Parlasca, M., & Mußhoff, O. (2020). Promises and pitfalls of digital credit: Empirical evidence from Kenya. *PLOS ONE*, 15(9), e0238747.

Jurek, D. (2023). Patents, innovation, and market entry. U.S. Census Bureau Working Paper CES-WP-23-45.

Kelishomi, A. M., & Nisticò, R. (2024). Economic sanctions and informal employment. *Labour Economics*, 83, 102431.

Kim, M., & Duvendack, M. (2025). Fintech for the poor? Regulating the Kenyan digital credit market and its impact on borrowers. *Development Studies Research*, 12(1).

Kimeu, C. (2022). 'Traumatising': how rogue digital loan apps in Kenya intimidate borrowers. *The Guardian*.

Klapper, L., Singer, D., Starita, L., & Norris, A. (2025). *The Global Findex Database 2025: Connectivity and Financial Inclusion in the Digital Economy*. Executive Summary. World Bank.

Malani, A., & Reif, J. (2015). Interpreting pre-trends as anticipation: Impact on estimated treatment effects from tort reform. *Journal of Public Economics*, 124, 1–14. https://doi.org/10.1016/j.jpubeco.2015.01.001

McKee, K., Kaffenberger, M., & Zimmerman, J. M. (2015, June). Doing digital finance right: The case for stronger mitigation of customer risks. Focus Note No. 103. CGAP.

Meager, R. (2019). Understanding the average impact of microcredit expansions: A Bayesian hierarchical analysis of seven randomized experiments. *American Economic Journal: Applied Economics*, 11(1), 57–91.

Moser, A., & Korstjens, I. (2018). Series: Practical guidance to qualitative research. Part 3: Sampling, data collection and analysis. *European Journal of General Practice*, 24(1).

Nelson, R. R. (1956). A theory of the low-level equilibrium trap in underdeveloped economies. *The American Economic Review*, 46(5), 894–908.

Ngugi, B. (2020). Suicide that jolted CBK: Inside plan to rein in digital lenders. *Daily Nation*.

Robinson, J., Park, D. S., & Blumenstock, J. E. (2022). The impact of digital credit in developing economies: A review of recent evidence. CEGA Working Paper Series No. WPS-192.

Starr, M. A. (2014). Qualitative and mixed-methods research in economics: Surprising growth, promising future. *Journal of Economic Surveys*, 28(2), 238–264.

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American Economic Review*, 71(3), 393–410.

Suri, T. (2021). Mobile money. In P. Njoroge & V. Murinde (Eds.), *50 Years of Central Banking in Kenya*. Oxford University Press.

Suri, T., Bharadwaj, P., & Jack, W. (2021). Fintech and household resilience to shocks: Evidence from digital loans in Kenya. *Journal of Development Economics*.

Tampuri, M. Y. (2023). Digital lending in emerging economies: The nexus between financial innovation and consumer protection. *American Journal of Finance and Accounting*, 7(2), 145–168.

Upadhyaya, R., Weitzberg, K., & Bonyo, L. (2024). Digital credit and regulation in Kenya. Manuscript.

Upadhyaya, R., Weitzberg, K., & Bonyo, L. (2025). Digital credit providers, regulatory frameworks, and structural power: A case study of digital microcredit regulation in Kenya. *Finance and Society*, 11(2), 186–208.

Wamalwa, P., Rugiri, I., & Lauler, J. (2019). Digital credit, financial literacy and household indebtedness. Kenya Bankers Association, Working Paper Series.

6 Appendix

List of participants

Session type	ID	Pseudonym
Interview	1	Researcher
Interview	2	Financial policy expert
Interview	3	Financial services user design expert
Interview	4	Data protection regulators
Interview	5	Credit information sharing expert
Interview	6	Competition regulator
Interview	7	Microfinance / digital financial services expert
Interview	8	The digital financial services expert
Interview	9	Senior manager at an asset-finance digital lender
Interview	10	Senior manager at a digital lender
Interview	11	Senior manager at a digital lender
Interview	12	Senior manager at the UN
Interview	13	Safari camp CFO and digital borrower
Interview	14	Field worker during FinAccess 2024
Interview	15	Beauty shop manager in Kibera
Interview	16	Employed at catering firm in Kibera
Interview	17	Student with beauty shop business in Kibera
Interview	18	Bank director, digital financial services
Interview	19	Senior managers at a credit reference bureau
Interview	20	Uber driver (1)
Interview	21	Uber driver (2)
Interview	22	Uber driver (3)
Interview	23	Uber driver (4)
Interview	24	Uber driver (5)
Interview	25	Uber driver (6)
Interview	26	Uber driver (7)
Interview	27	Uber driver (8)
Interview	28	Uber driver (9)
Focus group	1	Nannies and housekeepers
Focus group	2	Landscapers and guards

Table 2: Anonymized list of qualitative study participants

Note: All participants are identified by pseudonym only.

Table 3: Correlation matrix of digital app loan intensity

	County mean 2016	County mean 2019	County mean 2021
County mean 2016	1	.1152348	.1092518
County mean 2019	.1152348	1	.4686353
County mean 2021	.1092518	.4686353	1

Note: County-level means reflect the average digital app loan uptake in each county, measured as the share of respondents reporting digital app loan usage. Means are computed for 47 counties across three survey waves (2016, 2019, 2021). Correlation coefficients are Pearson.
Source: Author's rendering of FinAccess data (2016, 2019, 2021).

Methodology chapter

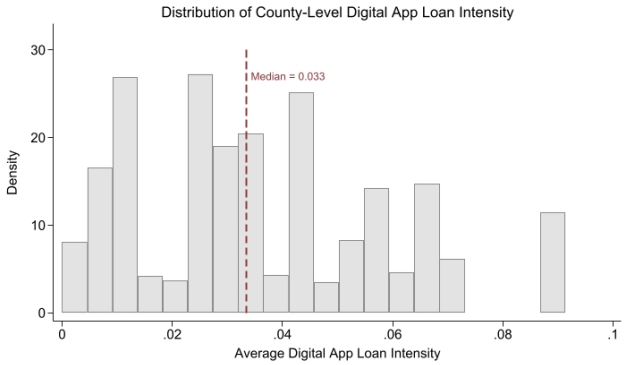

Figure 9: Density plot of Digital App Loan usage across counties with median.

Source: Author's rendering of FinAccess data (2021).

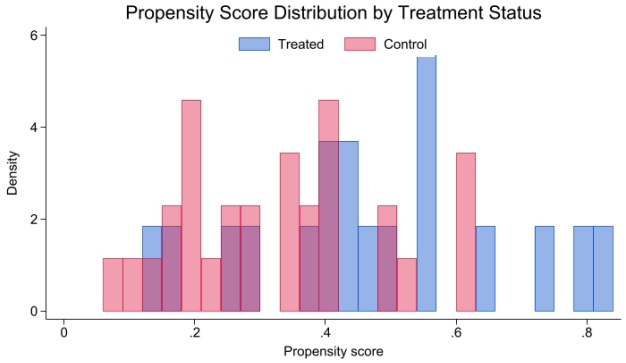

Figure 10: Common support check. Distribution plot of the propensity scores for treated and untreated counties.

Source: Author's rendering of FinAccess data (2016, 2019, 2021).

Table 4: Covariate Balance by Treatment Status

	Treated (unw.)		Control (unw.)		Treated (ATT)		Control (ATT)	
	mean	sd	mean	sd	mean	sd	mean	sd
Internet Access	0.314	(0.133)	0.254	(0.068)	0.314	(0.133)	0.286	(0.066)
Mobile Ownership	0.827	(0.068)	0.793	(0.066)	0.827	(0.068)	0.810	(0.053)
Urban	0.335	(0.259)	0.281	(0.159)	0.335	(0.259)	0.284	(0.164)
Education Level	2.442	(0.245)	2.269	(0.317)	2.442	(0.245)	2.416	(0.230)
Observations	18		29		18		29	

Notes: County-level means computed as survey-weighted averages. Treated (unw.) and Control (unw.) show unweighted group means. Treated (ATT) and Control (ATT) show means after applying inverse probability weights.

Source: Author's rendering of FinAccess data (2016, 2019, 2021).

Results chapter

Table 5: Event-Study Estimates: Treatment Effects by Year (With Controls)

Outcome	Year	Coef	SE	CI Low	CI High	p-value
Basic Needs Index	2019	-0.0678	0.0664	-0.2014	0.0659	0.3128
Basic Needs Index	2021	0.0282	0.0704	-0.1135	0.1699	0.6909
Basic Needs Index	2024	-0.0047	0.0595	-0.1244	0.1150	0.9375
Debt Distress Index	2019	0.0315	0.0394	-0.0479	0.1109	0.4285
Debt Distress Index	2021	0.0220	0.0330	-0.0443	0.0884	0.5070
Debt Distress Index	2024	-0.0732	0.0235	-0.1204	-0.0259	0.0031
Financial Resilience Index	2019	0.0060	0.0462	-0.0869	0.0990	0.8965
Financial Resilience Index	2021	0.0345	0.0274	-0.0207	0.0896	0.2146
Financial Resilience Index	2024	0.0075	0.0318	-0.0565	0.0714	0.8149
Digital App Loan Default	2021	0.0082	0.0047	-0.0013	0.0177	0.0907
Digital App Loan Default	2024	0.0061	0.0050	-0.0040	0.0161	0.2313

Notes: Estimates from a FE - DiD event-study with county and year fixed effects, estimated without controls. Standard errors are clustered at the county level.

Parallel trends: The parallel trends assumption is **supported** for: *Basic Needs Index*, *Debt Distress Index*, *Financial Resilience Index*, and *Digital App Default*.

Table 6: Event-Study Estimates: Treatment Effects by Year (Without Controls)

Outcome	Year	Coef	SE	CI Low	CI High	p-value
Basic Needs Index	2019	-0.0579	0.0711	-0.2010	0.0853	0.4200
Basic Needs Index	2021	0.0377	0.0714	-0.1061	0.1814	0.6005
Basic Needs Index	2024	0.0072	0.0626	-0.1189	0.1333	0.9094
Debt Distress Index	2019	0.0224	0.0421	-0.0624	0.1072	0.5970
Debt Distress Index	2021	0.0155	0.0351	-0.0552	0.0863	0.6603
Debt Distress Index	2024	-0.0817	0.0259	-0.1338	-0.0297	0.0028
Financial Resilience Index	2019	0.0042	0.0503	-0.0970	0.1054	0.9334
Financial Resilience Index	2021	0.0417	0.0298	-0.0183	0.1017	0.1683
Financial Resilience Index	2024	0.0150	0.0327	-0.0509	0.0809	0.6485
Digital App Loan Default	2021	0.0082	0.0047	-0.0013	0.0176	0.0890
Digital App Loan Default	2024	0.0059	0.0049	-0.0040	0.0159	0.2344

Notes: Estimates from a FE - DiD event-study with county and year fixed effects, estimated without controls.Standard errors are clustered at the county level.

Parallel trends: The parallel trends assumption is **supported** for: *Basic Needs Index*, *Debt Distress Index*, *Financial Resilience Index*, and *Digital App Default.*

Robustness chapter

Table 7: Robustness Check: Covariate Balance by Treatment Status with added covariates

	Treated (unw.)		Control (unw.)		Treated (ATT)		Control (ATT)	
	mean	sd	mean	sd	mean	sd	mean	sd
internet access	0.314	(0.133)	0.254	(0.068)	0.314	(0.133)	0.292	(0.068)
mobile ownership	0.827	(0.068)	0.793	(0.066)	0.827	(0.068)	0.810	(0.052)
urban	0.335	(0.259)	0.281	(0.159)	0.335	(0.259)	0.309	(0.188)
education level	2.442	(0.245)	2.269	(0.317)	2.442	(0.245)	2.418	(0.247)
financially literate	0.411	(0.122)	0.368	(0.110)	0.411	(0.122)	0.411	(0.094)
Observations	18		29		18		29	

Notes: County-level means computed as survey-weighted averages. Treated (unw.) and Control (unw.) show unweighted group means. Treated (ATT) and Control (ATT) show means after applying inverse probability weights.

Source: Author's rendering of FinAccess data (2016, 2019, 2021).

Table 8: Robustness Check: DiD Estimates with added covariates in IPW model

	Digital app defaults		Debt distress		Financial resilience		Basic needs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No controls	With controls	No controls	With controls	No controls	With controls	No controls	With controls
Treatment × Post	0.000	0.000	-0.088***	-0.083***	-0.003	-0.009	0.018	0.012
	(0.005)	(0.004)	(0.026)	(0.026)	(0.025)	(0.024)	(0.027)	(0.027)
employed		0.012***		-0.010		0.212***		0.137***
		(0.002)		(0.015)		(0.016)		(0.027)
farming		0.004**		0.088***		0.067***		-0.020
		(0.002)		(0.011)		(0.013)		(0.025)
casual_worker		0.009***		0.055***		-0.032*		-0.092***
		(0.003)		(0.012)		(0.018)		(0.021)
business		0.015***		0.059***		0.128***		0.053**
		(0.003)		(0.010)		(0.017)		(0.022)
money_support		0.004		0.031*		-0.051***		0.037*
		(0.003)		(0.016)		(0.015)		(0.021)
Constant	0.012***	0.003	0.209***	0.159***	0.361***	0.313***	0.603***	0.599***
	(0.001)	(0.002)	(0.005)	(0.012)	(0.004)	(0.015)	(0.005)	(0.020)
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47742.000	47742.000	37124.000	37124.000	55722.000	55722.000	55722.000	55722.000
R-squared	0.004	0.005	0.049	0.059	0.082	0.151	0.151	0.181
Clusters	47.000	47.000	47.000	47.000	47.000	47.000	47.000	47.000

Notes: County and year fixed effects included. Standard errors (in parentheses) are clustered at the county level
individual sampling weight × inverse probability weight (IPW).

* p<0.10, ** p<0.05, *** p<0.01.

Table 9: Robustness Check: Covariate Balance by Treatment Status with 2021 as Baseline

	Treated (unw.)		Control (unw.)		Treated (ATT)		Control (ATT)	
	mean	sd	mean	sd	mean	sd	mean	sd
internet access	0.388	(0.114)	0.287	(0.078)	0.388	(0.114)	0.359	(0.073)
mobile ownership	0.858	(0.062)	0.797	(0.081)	0.858	(0.062)	0.847	(0.058)
urban	0.363	(0.299)	0.197	(0.119)	0.363	(0.299)	0.289	(0.168)
education level	2.507	(0.262)	2.244	(0.387)	2.507	(0.262)	2.484	(0.300)
Observations	18		29		18		29	

Notes: County-level means computed as survey-weighted averages. Treated (unw.) and Control (unw.) show unweighted group means. Treated (ATT) and Control (ATT) show means after applying inverse probability weights.

Source: Author's rendering of FinAccess data (2021).

Table 10: Robustness Check: DiD Estimates with IPW Constructed from 2021 Baseline

	Digital app defaults		Debt distress		Financial resilience		Basic needs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No controls	With controls	No controls	With controls	No controls	With controls	No controls	With controls
Treatment × Post	-0.002	-0.002	-0.106***	-0.103***	-0.010	-0.018	0.016	0.011
	(0.006)	(0.006)	(0.021)	(0.020)	(0.025)	(0.024)	(0.026)	(0.027)
Employed		0.011***		-0.011		0.214***		0.138***
		(0.003)		(0.014)		(0.017)		(0.027)
Farming		0.006***		0.085***		0.071***		-0.009
		(0.002)		(0.010)		(0.014)		(0.019)
Casual Worker		0.010***		0.057***		-0.042*		-0.096***
		(0.003)		(0.011)		(0.022)		(0.025)
Business Owner		0.018***		0.065***		0.125***		0.055**
		(0.003)		(0.014)		(0.021)		(0.023)
Money Support		0.009**		0.043**		-0.053**		0.039*
		(0.003)		(0.019)		(0.021)		(0.023)
Constant	0.013***	0.002	0.205***	0.152***	0.358***	0.313***	0.622***	0.617***
	(0.001)	(0.002)	(0.004)	(0.010)	(0.004)	(0.018)	(0.004)	(0.021)
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47742.000	47742.000	37124.000	37124.000	55722.000	55722.000	55722.000	55722.000
R-squared	0.003	0.005	0.039	0.049	0.065	0.139	0.121	0.153
Clusters	47.000	47.000	47.000	47.000	47.000	47.000	47.000	47.000

Notes: County and year fixed effects included. Standard errors (in parentheses) are clustered at the county level. Weights: individual sampling weight × inverse probability weight (IPW). * p<0.10, ** p<0.05, *** p<0.01.

Table 11: Robustness Check: DiD Estimates only using 2021 and 2024

	Digital app defaults		Debt distress		Financial resilience		Basic needs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No controls	With controls	No controls	With controls	No controls	With controls	No controls	With controls
Treatment × Post	-0.004	-0.004	-0.121***	-0.119***	-0.043	-0.044*	-0.008	-0.008
	(0.006)	(0.006)	(0.030)	(0.029)	(0.027)	(0.024)	(0.039)	(0.041)
Employed		0.014***		-0.027		0.153***		0.111***
		(0.003)		(0.030)		(0.020)		(0.034)
Farming		0.007***		0.064**		0.040***		-0.039
		(0.002)		(0.025)		(0.015)		(0.030)
Casual Worker		0.012***		0.039		-0.088***		-0.122***
		(0.003)		(0.024)		(0.017)		(0.035)
Business Owner		0.021***		0.050**		0.054**		0.028
		(0.004)		(0.024)		(0.023)		(0.032)
Money Support		0.007**		0.007		-0.104***		0.029
		(0.003)		(0.025)		(0.018)		(0.024)
Constant	0.016***	0.004*	0.246***	0.217***	0.337***	0.350***	0.553***	0.571***
	(0.002)	(0.002)	(0.010)	(0.027)	(0.008)	(0.016)	(0.011)	(0.033)
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39801.000	39801.000	24614.000	24614.000	39801.000	39801.000	39801.000	39801.000
R-squared	0.004	0.005	0.044	0.052	0.040	0.125	0.105	0.139
Clusters	47.000	47.000	47.000	47.000	47.000	47.000	47.000	47.000

Notes: County and year fixed effects included. Standard errors (in parentheses) are clustered at the county level. Weights: individual sampling weight × inverse probability weight (IPW). * p<0.10, ** p<0.05, *** p<0.01.

Table 12: Robustness Check: Alternative Treatment Threshold (0.03)

	Digital app defaults		Debt distress		Financial resilience		Basic needs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No controls	With controls	No controls	With controls	No controls	With controls	No controls	With controls
Treatment × Post	0.007	0.007	-0.063**	-0.061*	0.041	0.042	0.013	0.011
	(0.006)	(0.006)	(0.031)	(0.032)	(0.049)	(0.045)	(0.033)	(0.031)
Employed		0.013***		-0.009		0.211***		0.158***
		(0.002)		(0.013)		(0.017)		(0.025)
Farming		0.004**		0.072***		0.073***		0.009
		(0.002)		(0.013)		(0.012)		(0.026)
Casual Worker		0.009***		0.050***		-0.033**		-0.068***
		(0.002)		(0.011)		(0.015)		(0.021)
Business Owner		0.012***		0.056***		0.130***		0.069***
		(0.003)		(0.009)		(0.015)		(0.020)
Money Support		0.009		0.027**		-0.049***		0.057**
		(0.006)		(0.013)		(0.013)		(0.021)
Constant	0.010***	0.001	0.193***	0.149***	0.357***	0.306***	0.618***	0.593***
	(0.001)	(0.003)	(0.006)	(0.013)	(0.009)	(0.014)	(0.006)	(0.021)
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47742.000	47742.000	37124.000	37124.000	55722.000	55722.000	55722.000	55722.000
R-squared	0.003	0.004	0.049	0.057	0.079	0.145	0.144	0.172
Clusters	47.000	47.000	47.000	47.000	47.000	47.000	47.000	47.000

Notes: County and year fixed effects included. Standard errors (in parentheses) are clustered at the county level. Weights: individual sampling weight × inverse probability weight (IPW). * p<0.10, ** p<0.05, *** p<0.01.

Table 13: Robustness Check: Alternative Treatment Threshold (0.05)

	Digital app defaults		Debt distress		Financial resilience		Basic needs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No controls	With controls	No controls	With controls	No controls	With controls	No controls	With controls
Treatment × Post	-0.001	-0.001	-0.115***	-0.110***	-0.012	-0.018	0.025	0.017
	(0.004)	(0.004)	(0.020)	(0.019)	(0.027)	(0.026)	(0.028)	(0.028)
Employed		0.013***		-0.013		0.208***		0.142***
		(0.003)		(0.019)		(0.019)		(0.029)
Farming		0.006***		0.087***		0.068***		-0.008
		(0.002)		(0.011)		(0.016)		(0.024)
Casual Worker		0.011***		0.057***		-0.040*		-0.089***
		(0.003)		(0.011)		(0.021)		(0.023)
Business Owner		0.016***		0.057***		0.124***		0.064***
		(0.004)		(0.011)		(0.020)		(0.024)
Money Support		0.005		0.039**		-0.050***		0.052***
		(0.003)		(0.017)		(0.017)		(0.019)
Constant	0.013***	0.003	0.215***	0.165***	0.368***	0.322***	0.615***	0.602***
	(0.001)	(0.002)	(0.004)	(0.012)	(0.005)	(0.018)	(0.005)	(0.022)
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47742.000	47742.000	37124.000	37124.000	55722.000	55722.000	55722.000	55722.000
R-squared	0.004	0.005	0.051	0.061	0.071	0.144	0.134	0.166
Clusters	47.000	47.000	47.000	47.000	47.000	47.000	47.000	47.000

Notes: County and year fixed effects included. Standard errors (in parentheses) are clustered at the county level. Weights: individual sampling weight × inverse probability weight (IPW). * p<0.10, ** p<0.05, *** p<0.01.

Table 14: Robustness Check: Placebo test using 2020 as treatment year

	Digital app defaults		Debt distress		Financial resilience		Basic needs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No controls	With controls	No controls	With controls	No controls	With controls	No controls	With controls
Treatment × Post	-0.004	-0.003	-0.074*	-0.066*	-0.018	-0.026	0.093**	0.087**
	(0.005)	(0.005)	(0.037)	(0.036)	(0.031)	(0.028)	(0.040)	(0.041)
Employed		0.008***		-0.013		0.214***		0.112***
		(0.003)		(0.015)		(0.018)		(0.035)
Farming		0.003		0.086***		0.065***		-0.034
		(0.002)		(0.018)		(0.014)		(0.035)
Casual Worker		0.008**		0.065***		-0.024		-0.104***
		(0.003)		(0.013)		(0.015)		(0.023)
Business Owner		0.013***		0.054***		0.142***		0.039
		(0.003)		(0.011)		(0.020)		(0.028)
Money Support		0.005		0.043**		-0.046***		0.007
		(0.003)		(0.020)		(0.015)		(0.027)
Constant	0.012***	0.005	0.208***	0.154***	0.382***	0.328***	0.630***	0.646***
	(0.002)	(0.003)	(0.007)	(0.010)	(0.007)	(0.016)	(0.009)	(0.028)

Notes: County and year fixed effects included. Standard errors (in parentheses) are clustered at the county level. Weights: individual sampling weight × inverse probability weight (IPW). * p<0.10, ** p<0.05, *** p<0.01.